# Understanding User Engagement with Cross-Platform Social Media Content Created by Humans Versus AI: An Evaluation of ChatGPT in Content Marketing

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Even though generative artificial intelligence (GenAI) is increasingly integrated into user-facing technologies like social media, its impact on content marketing remains unverified. Early evidence suggests that language models (LLMs) can generate content that rivals human-created content (HCC) in terms of appeal. However, the question of adapting such content for various social media platforms remains unanswered. This study examines the effectiveness of an LLM, GPT-4, in customizing cross-platform content for Facebook, Instagram, and X. A total of 892 participants evaluated 30 pairs of AI-created content (ACC) and HCC. The findings reveal that ACC was preferred by users, delivered stronger calls to action, and elicited more user engagement than HCC, especially on Facebook, with a less pronounced effect for shorter posts on X and Instagram. We further generated six data-driven user personas of the 892 participants, illustrating the differences between those who preferred ACC or HCC on the three platforms. The results indicate that GPT-4 can adapt content to platform-specific requirements and maintain high perceived quality, making LLMs applicable for cross-platform content creation for user engagement. Findings contribute to understanding user engagement with AI-generated content across platforms. We also discuss the role of LLMs in content creation, including their ethical implications.

CCS Concepts: • **Human-centered computing → Collaborative content creation**; **Social media**.

Additional Key Words and Phrases: Social media, Facebook, Instagram, X, Generative AI

## 1 Introduction

Social media platforms are important for users in communicating, sharing, and engaging with online content from companies, other organizations, and friends and family [18, 94]. Platforms such as Facebook (FB), Instagram (IG), and X offer distinct communication styles for individuals and businesses to achieve their goals through content creation and branding [37, 55, 113]. At the same time, these communication styles present challenges for creating effective content [5] that meets the styles (and limitations, such as length requirements) of multiple platforms. For this reason, many organizations strive to maximize their reach by employing *cross-platform content creation*, which refers to adapting or tailoring the generated content to each targeted social media platform [72, 104]. So,

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ACM 1559-114X/2026/4-ART
https://doi.org/10.1145/3756014

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*cross-platform content* involves adapting digital content—such as social media posts, text, images, and videos—to align with a social media platform's specific audience expectations and communication styles (e.g., short vs. long, formal vs. informal). This adaptation is labor-intensive and requires a solid understanding of the differences between the platforms.

Generative artificial intelligence (GenAI) offers innovative ways to create *tailored* cross-platform content for various social media platforms, particularly by using large language models (LLMs) [38]. LLMs, such as OpenAI's GPT-4, exhibit proficiency in comprehending and generating text [31], leading to increased use in creating social media content [4, 21]. The interaction of users with *AI-created content* (ACC) has garnered significant attention in disciplines such as computer science, consumer psychology, and marketing [15, 17, 21, 48, 104]. However, several questions remain unanswered: *How effectively can LLMs produce engaging cross-platform content?*, *How does ACC compare to human-created content (HCC) impact users emotionally?*, and *What are the broader effects of ACC on social media users' engagement and preferences?* Although previous studies mention cross-applicability of LLMs for online content creation [48, 97, 104], much remains to be understood about AI's cross-platform content creation capabilities. In addition, it is important to understand the segments of social media users that prefer ACC over HCC (or *vice versa*).

This study investigates how content generated by an LLM, specifically OpenAI's GPT-4, performs across different social media platforms and examines its impact on different levels of user engagement (UE) [8] and emotional response [9]. We collect empirical data from actual social media users and conduct a comparative analysis between *ACC* and *HCC* on three major social media platforms: FB, IG, and X. This analysis investigates the effectiveness of LLMs in social media content marketing. Given that each platform has distinct content requirements essential for successful content marketing [73] (see Section 2.1), we present the following motivational question: *Can LLMs create engaging content? Specifically, can such content effectively capture the distinctive demands of FB's expansive user base, IG's image-centric approach, and X's concise, rapid communication style?* This question is critical for the social media marketing community, content marketers, and researchers, as leveraging LLMs for content customization may improve both the effectiveness and efficiency of social media content creation [97, 104].

Based on the motivation outlined above, this study addresses the following research questions (RQs):

- **RQ1:** *To what extent can ACC, relative to HCC, effectively fulfill the unique user engagement expectations of specific social media platforms?*
- **RQ2:** *How do emotional responses elicited by ACC differ from those elicited by HCC?*
- **RQ3:** *How does user engagement with ACC differ from engagement with HCC?*
- **RQ4:** *Do users prefer ACC or HCC?*
- **RQ5:** *How do users who prefer ACC compare with users who prefer HCC?*

These RQs address critical aspects of LLMs content performance within social media marketing. RQ1 examines LLMs' capability to produce content that aligns with platform-specific constraints such as length, visual orientation, and tone. RQ2 explores whether AI-generated content can evoke genuine emotional engagement, which remains essential for content effectiveness. RQ3 focuses on engagement metrics, because audience reactions and interactions are of primary importance for organizations doing content marketing [48]. RQ4 investigates user preferences, including attitudes, perceptions, and content affinity [5, 9], determining whether AI-generated content can meaningfully contribute to marketing effectiveness. Finally, RQ5 seeks to identify key audience traits associated with preferences for either content type, which is crucial for optimizing cross-platform content creation [36, 95].

We formalize our expectations for the empirical investigation through specific hypotheses (see Table 1). Our overarching expectation, applied implicitly and consistently across each individual hypothesis, is that "ACC will perform better than HCC." This expectation is grounded in accumulating evidence demonstrating that LLMs

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achieve human-level performance on diverse tasks [11, 97]. Specifically, the hypotheses are consistent with nascent research indicating the substantial capabilities of LLMs in generating digital content [38].

Table 1. Research questions and corresponding hypotheses.

| **RQ1: Platform-specific adaptability** | **RQ2: Emotional responses** | **RQ3: User engagement** | **RQ4: User preference** |
|---|---|---|---|
| • **H01:** ACC has greater topical relevance than HCC.<br>• **H02:** ACC has superior clarity compared to HCC.<br>• **H03:** ACC has a more appropriate tone relative to HCC.<br>• **H04:** ACC has more effective calls to action (CTA) than HCC. | • **H05:** ACC has stronger positive emotional responses from users than HCC. | • **H06:** ACC results in more reads than HCC.<br>• **H07:** ACC results in more views than HCC.<br>• **H08:** ACC results in more likes than HCC.<br>• **H09:** ACC generates more comments than HCC.<br>• **H10:** ACC will be shared more frequently than HCC. | • **H11:** Users will exhibit a greater preference for ACC than for HCC. |

To empirically investigate our RQs, we conducted a user study in which participants evaluated ACC against HCC across three widely used social media platforms—FB, IG, and X. Participants assessed each post's adaptability to platform-specific requirements, emotional impact, engagement potential, and overall preference, without being informed whether the content was created by a human or by a LLMs. Our findings offer implications for diverse stakeholders, including content marketers, media and news organizations, political campaigners, non-profit entities, and advertising agencies. The results are especially relevant to the "digital creator" economy, valued annually at $14 billion USD [26], comprising content professionals such as authors, podcasters, visual artists, and musicians who leverage social media to reach their audiences and monetize their creative work. Given that LLMs are currently reshaping the digital content industry, empirical studies are essential for understanding their effects.

This journal paper extends our previously published work [4] by generating personas for the 892 participants and examining the differences between individuals who preferred either ACC or HCC. Specifically, for this work, we created AI chat-based personas that we interviewed to generate qualitative insights into their preferences for ACC or HCC.

## 2 Literature Review

### 2.1 Platform Specific Differences in Online Content

To reach a larger audience, content creators, including organizations and individuals, frequently create and publish the same content across various social media platforms—termed *cross-platform content creation* [76]. This practice allows for the efficient management of multiple social media accounts and regularly disseminating

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updated content. This process may involve customizing the content to align it effectively with the requirements of each platform, thereby aiming at increased UE [46, 77, 87]. Specifically, FB appeals to users who prioritize meaningful interpersonal connections, likely due to the platform's emphasis on community interactions [88]. IG, in contrast, emphasizes visual aesthetics and lifestyle presentation, attracting users concerned with self-promotion and personal branding, often reflected through personality-driven content [88]. X is primarily oriented toward concise updates and timely information, characterized by brief and direct text communication [44]. These distinct platform characteristics shape user expectations and influence their engagement behaviors [81]. For example, a study of slang content on Instagram and TikTok during a seven-year period revealed that unique digital expressions emerge [81] on the platforms. Other work shows that edge-based adaptive delivery systems improve performance and responsiveness in dynamic content environments [40].

Content that engages users on one platform does not necessarily achieve equivalent engagement on another, even if the content is essentially identical [6]. Although cross-posting identical content may occasionally amplify engagement, this effect varies substantially by the specific content and platforms involved [6, 10]. Generating tailored and engaging content for multiple platforms typically requires considerable time and effort, which creates demand for tools and processes that facilitate cross-platform content creation [5, 75]. Echoing this sentiment, Hollebeek et al. [48] discuss the emerging concept of consumer engagement powered by LLMs. An analysis of content from more than one thousand news outlets on FB and YouTube over a six-year period found that most content has minimal impact on engagement and rarely drives sustained growth [98].

LLMs, such as GPT-4, demonstrate proficiency in language understanding and production, enabling them to interpret nuanced contexts and generate text aligned with specific communication objectives [83, 101, 108]. This linguistic capability, derived from extensive training in diverse textual corpora, positions LLMs as potentially transformative in the domain of content creation on multiple digital platforms. However, social media platforms such as FB, IG, and X each maintain distinct content ecosystems with unique linguistic patterns and stylistic conventions that influence user interactions and overall engagement [7]. Some prior research shows only a weak correlation between demographics and platform usage behavior, implying that engagement with social media content is driven by factors other than demographics [86]. Other prior work shows differences in how people react to AI-generated content [91, 106].

Accordingly, a significant challenge for LLMs lies in the ability to align content generation with various platform-specific requirements, which can be formal or informal requirements. These requirements include dimensions such as content characteristics and engagement levels. Content characteristics include topical relevance, message clarity and tone appropriateness, and the effectiveness of CTA, each of which possibly impacts key content marketing performance indicators or engagement levels, including views, likes, comments, and shares [10, 103].

While studies have demonstrated that LLMs possess proficiency in adapting to varied writing styles and contextual nuances [2, 28, 62, 69], there is limited empirical evidence regarding their capacity to meet the content demands and audience expectations specific to individual social media platforms. To bridge this gap, we advance H01–H04, proposing that ACC may demonstrate enhanced adaptability to platform-specific characteristics, thereby potentially surpassing HCC in overall content marketing effectiveness.

Salvi et al. [97] provide evidence indicating that GPT-4 exhibits a superior ability to convince individuals in a debating context compared to human interlocutors, particularly when equipped with personalized information about the persuasion target. These results suggest promising possibilities for employing LLMs to enhance engagement in content marketing. However, the authors also raise significant concerns regarding LLMs adoption, specifically the risk of using LLMs to create personalized and persuasive yet potentially misleading content. In this research, we explicitly refrain from using any personal user data, thus circumventing ethical issues related to the use of sensitive personal information to personalize content [90]. Instead, our approach incorporates platform-specific guidelines directly within the prompts given to GPT-4, enabling content customization tailored to distinct

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social media contexts. This method aims to maintain content relevance and adaptability while simultaneously preserving user privacy, offering a robust alternative to personalization that accesses individual user information.

## 2.2 The Role of Emotions in Online Content

Emotions deeply influence how individuals define their humanity, express themselves, and interact socially [50, 70]. Studies of emotional contagion indicate that social media users often mirror the emotional tone of the content they consume, with such content subsequently shaping their own emotional states [65]. Specifically, positively framed content tends to encourage users to further share positive emotions [65], whereas exposure to negatively charged posts may provoke corresponding negative emotional responses [42].

On social media, emotional expression is particularly pronounced, revealing personal insights into the private and public dimensions of people's lives, thoughts, and activities [63, 64, 84]. Given that emotional states profoundly shape daily behaviors, beliefs, and motivations [50], comprehending emotional responses is essential for understanding UE on social media [27, 112]. Indeed, social media content regularly elicits emotional reactions from audiences, prompting expressive interactions such as comments or other behavioral responses [111]. Identifying and interpreting online emotional responses is also critical for mitigating challenges in digital social environments, including issues like radicalization and misinformation [71], particularly during times of crisis or instability [3, 49, 93, 99].

In terms of emotions, LLMs exhibit capabilities in sentiment and emotion classification that rival specialized systems like IBM Watson, even without targeted training in these specific tasks [23]. Moreover, emotional analysis performed by LLMs has been found to closely reflect human emotional judgments [107]. Although the emotional characteristics of ACC have begun receiving attention [33], comparative studies assessing the emotional depth of ACC versus HCC, particularly within the context of social media, remain scarce. This gap presents an important research opportunity to examine how effectively ACC captures emotional nuances relative to HCC. Motivated by this gap, H05 posits that ACC may generate stronger positive emotional responses than HCC.

## 2.3 User Engagement and Online Content

UE is a multifaceted phenomenon shaped by numerous factors, including the specific context, the nature of the content, and the attributes of the content creator [51, 74, 78]. Defined as "the emotional, cognitive, and behavioral connection established between a user and a resource at any given moment, potentially extending over time," UE encompasses interactions with digital applications or content [14]. Consistent with prior research, our study operationalizes UE by measuring observable user behaviors and interactions [13, 53, 67]. Within the social media domain, quantifiable engagement indicators such as likes, comments, and shares serve as key metrics for organizations to evaluate the effectiveness of their content [89], with certain behaviors being more prevalent. For instance, users are more inclined to click on a post's link or like it rather than comment, as the former actions require less effort [25, 68]. Comprehending these engagement behaviors is vital for organizations because they offer audience feedback and represent an indirect form of user contribution [47]. Consequently, understanding these behaviors can improve organizational performance in areas such as sales growth and cost reduction [43, 66].

The labeling of AI-generated advertisements has been shown to significantly affect UE behaviors [33]. Considering this, the present study employs an experimental method where participants view two sequential versions of identical social media posts—one created by AI (i.e., ACC) and the other by humans (i.e., HCC)—without disclosing their origins. This design independently enables a precise assessment of engagement metrics for each type of content. However, comparative analyses examining UE with ACC versus HCC across multiple social media platforms remain scarce in the existing literature, implying a need for the current study.



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Prior research suggests an interplay between content attributes and UE behaviors [10]. Accordingly, hypotheses H06–H10 examine whether ACC, leveraging its adaptability to platform-specific contexts and capacity for emotional resonance, can surpass HCC in fostering UE.

Natural Language Generation (NLG) technologies have reached a stage where LLMs-created texts frequently appear indistinguishable from those authored by humans. Prior studies [20, 61] illustrate this capability by showcasing the naturalness of texts produced using contemporary NLG approaches. Empirical evidence further demonstrates that individuals frequently face challenges distinguishing AI-created from human-authored content, often failing to accurately identify the true origin [56, 109]. Henestrosa et al. [45] reported no significant differences in perceived credibility or trustworthiness between AI-generated and human-written texts. However, Rezwana and Maher [92] examined interactions between humans and AI, discovering that AI-to-human communication improves UE, collaboration quality, and perceptions of AI as reliable, intelligent, and personable. As such, we advance H06-H10; ACC will outperform HCC.

# 3 Methodology

## 3.1 Overview

Building on the concept of cross-platform content creation, this study investigates how a LLM, GPT-4 can support creating engaging content tailored to multiple social media platforms. Using GPT-4's capabilities in language comprehension and text generation, we empirically assess the model's utility in creating content for different social platforms. Specifically, we examine GPT-4's ability to adapt to the unique requirements of each platform, generate content with emotional resonance, and influence overall UE and perception.

## 3.2 Participants

To obtain a diverse and representative sample of participants suitable for addressing our RQs, we recruited 892 participants through CloudResearch, an established online participant recruitment platform [24]. The invitations targeted social media users based in the United States who met two eligibility criteria: (1) active engagement with at least one of the social media platforms examined (FB, IG, or X); (2) current participation in employment (full-time, part-time, or self-employed) or enrollment in educational programs. We ensured a balanced sample for each of the investigated social media platforms. For FB, our sample comprised 301 active users ($M_{age}$ = 41.76 years), of whom 36.88% (n = 111) were male, and 63.12% (n = 190) were female. On average, participants reported spending 4.58 hours per day on the platform. For IG, our sample included 305 active users ($M_{age}$ = 48 years). Among these participants, 40.66% ($n$ = 124) identified as male, and 59.34% ($n$ = 181) as female. Participants reported spending an average of 5.02 hours daily on IG. For X, the sample consisted of 286 regular users ($M_{age}$ = 41.81 years). Among these participants, 42.66% (n = 122) were male, and 57.34% (n = 164) were female. On average, participants reported spending 5.19 hours per day on the platform.

## 3.3 Procedure

We initially collected and prepared 90 pairs of HCC and ACC, comprising 30 pairs for each platform (FB, IG, and X). Each set represented 30 cross-platform posts, with every post shared across the three distinct platforms. Figure 1 provides examples that illustrate three pairs of HCC and ACC, one pair for each platform. We conducted three surveys, each customized for a specific social media platform, using the Qualtrics survey platform. The detailed study pipeline is presented in Figure 2. Each participant evaluated content exclusively from one platform—FB, IG, or X— aligned with their platform usage.

To verify participant attentiveness and genuine engagement, we embedded 30 attention-check questions, distributing one question per post. Participants who failed any of these quality-control checks were excluded

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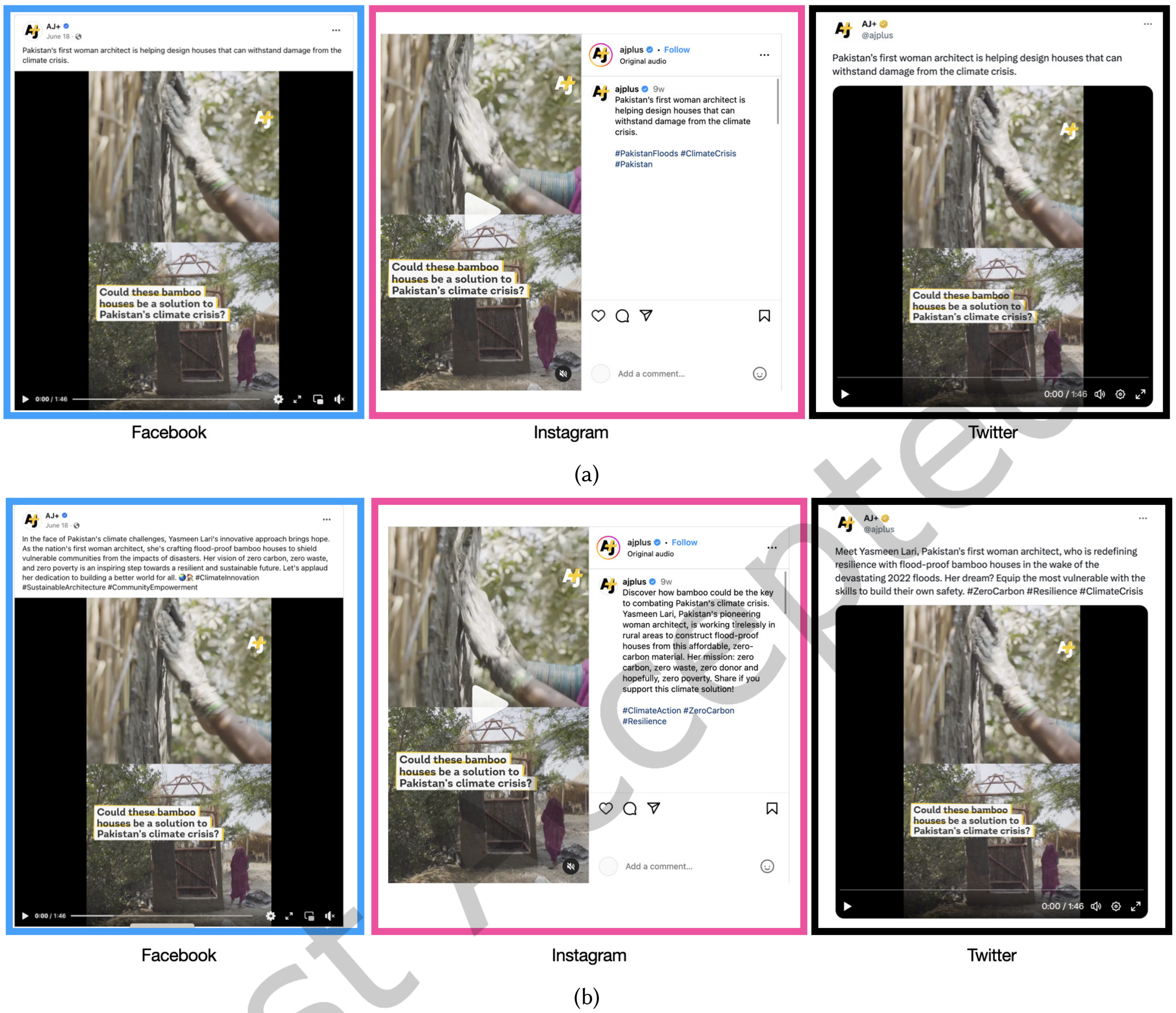


Fig. 1. Sample social media content from a major international news agency on FB, IG, and X: (a) is the HCC for each platform, and (b) is the ACC for each platform.

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from the analysis. Following informed consent, the participants evaluated three content posts relevant to their active platform.

This research used a within-subjects experimental design [41, 60], where each participant viewed two versions of a social media post—one HCC and one ACC—linked to the same video, specific to a single social media platform. The order in which participants viewed these posts was counterbalanced across the sample. The participants were instructed to read each post and provided a link to the corresponding original video. Importantly, participants remained unaware of each post's origin (human or GPT-4). This methodological choice ensured that each participant's evaluation formed a paired comparison between ACC and HCC, directly associated with identical content on the same platform.

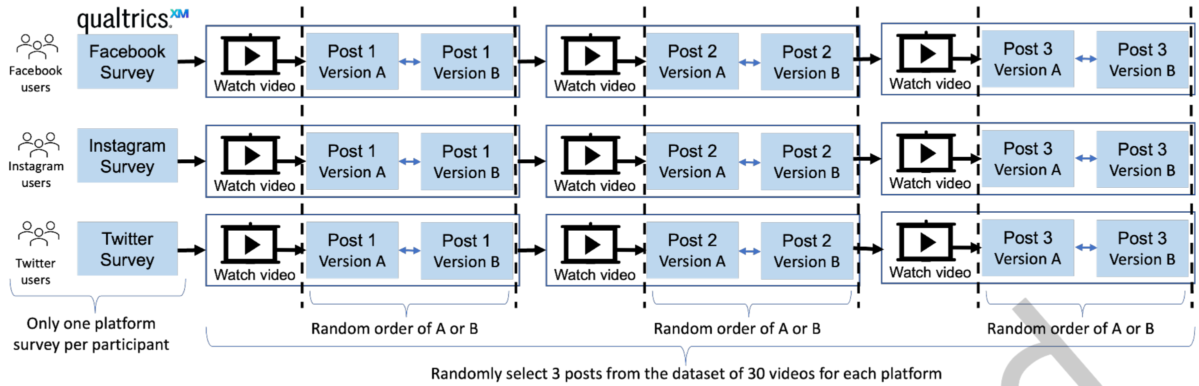


Fig. 2. The study pipeline shows the process of FB, IG, and X users starting the Qualtrics corresponding survey. Each participant sees three randomly selected content. Each post has a video, version A, HCC, and version B, ACC, which is displayed to users randomly.

The participants viewed three randomly selected posts from a total pool of 30 available posts. Applying Qualtrics' balanced distribution feature, we ensured that each post was evaluated by approximately an equal number of participants and appeared equally often in different presentation orders. Specifically, each post was assessed an average of 30.1 times on FB, 30.5 times on IG, and 28.6 times on X.

### 3.4 Data Collection

*Video Content:* We constructed a dataset comprising 30 video clips, each cross-posted to FB, IG, and X, originally published between May and July 2023, sourced from a prominent international news and media organization, *AJ+ English*, with a strong emphasis on social media engagement and cross-platform content strategies. The selection of FB, IG, and X was driven by their widespread popularity and diverse user demographics, ranking as the top three social media platforms at the time of data collection[1]. Our exclusive focus on video content aimed to minimize potential biases arising from varying content types [7].

*AJ+ English* is recognized for its innovative approach to journalism and its use of digital platforms to engage a global audience. AJ+ typically covers impactful news topics, often addressing social issues through a format appealing to younger demographics. At the time of our study, AJ+ English had 11M followers on FB, 947,000 followers on IG, and 1.2M followers on X. The selected videos were identical across platforms, accompanied by uniform or customized textual descriptions and captions. Figure 1a presents examples of HCC from FB, IG, and X.

The engagement metrics for identical video content vary considerably across FB, IG, and X, consistent with previous studies [6]. Specifically, we observed the following average engagement metrics: On FB, posts received an average of 4,173 likes (Median=156), 445 comments (Median=27), and 1,002 shares (Median=48) (Figure 3a). On IG, posts garnered an average of 7,007 likes (Median=3466), 116 comments (Median=73), and 1,420 shares (Median=621)(Figure 3b). On X, the average engagement per post was lower, with 117 likes (Median= 73), 5 comments (Median=2), and 63 shares (Median=30) (Figure 3c).

*Video Transcription:* We transcribed all 30 videos into text format to provide input suitable for GPT-4, as this model processes text inputs. A sample video transcript of the sample social media posts in Figure 1 is shown in Appendix A. The average length of a video transcript was approximately 493 words (2,998 characters). The

[1]https://www.similarweb.com/top-websites/united-states/computers-electronics-and-technology/social-networks-and-online-communities/

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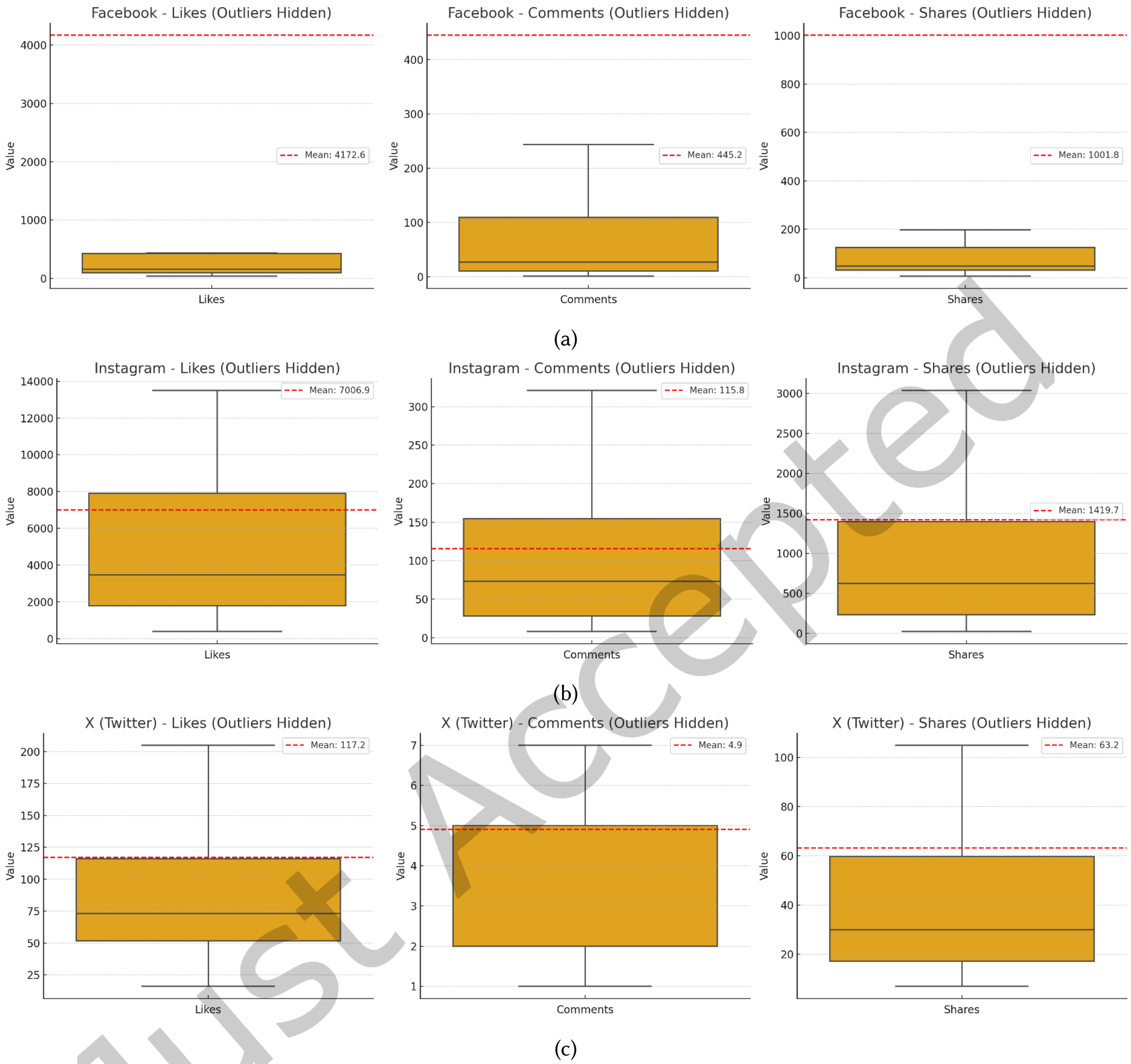


Fig. 3. The box plots of the distribution of engagement metrics across 30 video content and three platforms: (a) FB, (b) IG, and (c) X. The engagement metrics are likes, comments, and shares. Outliers are removed from the box plots for better illustration.

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length of the transcript varied considerably across the dataset, with the shortest transcript comprising 186 words (1,093 characters) and the longest reaching 1,122 words (6,722 characters). All transcripts were manually verified to ensure consistency with the respective video content. For videos containing non-English dialogue, translated text was incorporated into the transcripts. Given that GPT-4 had, at the time of the study, a limit of 32,000 tokens, our longest transcript, comprising 1,122 words, remained within this limit.

*GPT-4 Prompting:* There are two primary approaches to prompting GPT-4 for cross-platform content generation: the *individual platform prompt*, which generates content for each platform separately, and the *combined prompt*, which creates a uniform post tailored for multiple platforms simultaneously. In this study, we adopted the combined prompt approach. Specifically, we designed a structured prompt instructing GPT-4 to generate a post for X, a caption for IG, and a post for FB based on the same video transcript. The prompt was as follows: *Please provide a Twitter tweet, an Instagram caption, and a Facebook post suitable for video content based on the following transcript: [transcript]* The prompt used in this study refers to Twitter rather than X, as it was formulated in August 2023, shortly after the platform's rebranding. At that time, the GPT-4 model used in this research had not yet incorporated the name change. This concatenated prompt, along with the respective video transcript, was provided to GPT-4. Given that our dataset included 30 videos, this process was repeated 30 times—once per transcript—to produce ACC for all three platforms.

For FB, the response was extracted as a more descriptive and contextually engaging post tailored to the platform's user expectations and content dynamics. For IG, the output emphasized engagement-driven language, encouraging actions such as swiping left or clicking the video link to increase interaction. For X, the first segment of the response was selected, ensuring compliance with X's character limit. Across all three platforms, ACC included hashtags, which play a crucial role in categorizing posts, improving discoverability and UE. Figure 1b presents an example of LLMs cross-platform content for FB, IG, and X. To ensure the ACC aligned with our research objectives, we performed a manual review to remove action-related text irrelevant to the study. Despite specifying in the prompt that the content was for a video post, some IG captions (5 out of 30) still included directives such as "*Swipe ⇒" or "[link to the video].*" Since these elements were not pertinent to our analysis, they were manually removed. For each video, we first captured a screenshot of the HCC as it appeared on its respective platform. Then, we replaced the post text with the AI-generated version and took another screenshot to create the survey (see Figure 1). To avoid any social influence on participants' evaluations, engagement metrics such as likes, comments, and shares were hidden. Additionally, we ensured that both versions—ACC and HCC—maintained the same visual format, differing only in the text content.

## 3.5 Measures

*Platform Adaptability:* To address RQ1, platform adaptability was assessed based on four key dimensions: topical interest, clarity, tone, and call to action (CTA). Participants rated each dimension using a five-point semantic differential scale through the following survey questions:

- Topical Interest: Participants evaluated how engaging they found the topic of the content, using a scale of *Not Interesting* (1) to *Very Interesting* (5).
- Clarity: Participants rated the clarity of the text from *Very unclear* (1) to *Very clear* (5).
- Tone: Participants assessed the tone of the content, ranging from *Very informal* (1) to *Very formal* (5).
- CTA: Participants rated the effectiveness of the CTA—statements prompting engagement (e.g., liking, commenting, sharing)—on a scale from *Very weak* (1) to *Very strong* (5).

*Emotional Response:* To address RQ2, we examined participants' emotional responses to HCC and ACC by assessing general sentiment (positive or negative) [22]. Participants were asked: "How did the post make you feel?" Responses were recorded using a five-point Likert scale, ranging from 1 (Very negative) to 5 (Very positive), allowing for a comparative analysis of emotional reactions to ACC and HCC.

*Engagement:* To measure UE (RQ3), we incorporated both consumption-based metrics (e.g., views and reads) and contribution-based metrics (e.g., likes, comments, and shares) [32, 100]. Engagement was assessed through a series of questions in which participants rated their likelihood of interacting with the content. The responses were collected using a five-point Likert scale, ranging from 1 (Very unlikely) to 5 (Very likely). Participants were asked to evaluate their likelihood of (1) reading the post, (2) viewing the video based on the post content, (3) liking

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the post, (4) commenting on the post, and (5) sharing the post. These measures allowed for a direct comparison between ACC and HCC in terms of their ability to drive UE.

*User Preferences:* To address RQ4, we measured participants' post preference by presenting them with paired content—one HCC and one ACC. For each pair, participants answered the following question: *"If you had to select, which of the two posts do you prefer?"* Their responses allowed us to assess the general user preference, determining whether ACC or HCC was more favored across different social media platforms.

*Differences Between ACC and HCC Preference Users:* To address RQ4, we generated six personas of the survey participants, two for each platform, based on preference for ACC and HCC to understand the users better. For this purpose, we used an AI-driven persona generation system, *Survey2Persona (S2P*, publicly available at https://s2p.qcri.org), a state-of-the-art algorithmic persona tool [57]. Personas are data-driven, fictional representations of target users, customers, or audiences designed to improve user understanding [54, 79, 80]. These personas serve as a shared reference point within organizations [54]. Personas also support cognitive engagement for decision-makers [96] and provide a humanized representation of numbers, including survey data such as what we used in this research. As such, personas a valid approach for addressing RQ5.

S2P is an advanced system that converts survey data and similar structured datasets into actionable, user-centered personas, making it valuable for user research, social science, and business applications such as user experience and product development [57]. S2P uses Retrieval Augmented Generation (RAG) combined with an LLM—specifically OpenAI's GPT-4o at the time of this study—enabling users to engage in dynamic conversations with personas, thereby making the persona-user interaction more immersive and human-like. In addition to the typical persona profiles, S2P has a dialogue feature enabling one to chat directly with the personas [58], and each persona responds based solely on the data used to create it. We will use this feature to "interview" the personas for additional insights.

We used survey data from the previous analysis to generate personas by platform using S2P, based on whether or not the persona preferred ACC or HCC (see Figure 4). Then, we conversed with each of the six generated personas to uncover the underlying reasons for their attitudinal preferences toward ACC or HCC (see Figure 5, enriching the quantitative findings presented with qualitative insights derived from the survey data [59].

We then queried each persona in an LLM chat more, using the prompt "[Salutation], why do you prefer [ACC/HCC] on [FB,IG, X]?" for a total of six responded, ACC or HCC on each of the three platforms, FB,IG, and X.

## 4 Results

### 4.1 RQ1: To what extent can ACC, relative to HCC, effectively fulfill the unique user engagement expectations of specific social media platforms?

**H01. ACC has greater topical relevance than HCC.** A Wilcoxon signed-rank test was performed to compare topical relevance scores between HCC and ACC across FB, IG, and X. The results for FB revealed that ACC received significantly higher topical relevance ratings than HCC (W = 20701.0, p = 0.001). However, the differences for IG and X were not statistically significant (see Table 2). *Thus, H01 is supported for FB only, indicating that ACC demonstrates higher topical relevance than HCC on FB but not on IG or X.*

**H02. ACC has superior clarity compared to HCC.** For FB, the results indicated that ACC had higher clarity scores than HCC, W = 17957.0, p <0.001. The IG and X results were non-significant (see Table 2). Thus, *H02 is supported for FB only: ACC shows superior clarity than HCC on FB but not on IG or X.*

**H03. ACC has a more appropriate tone relative to HCC.** For FB, the results indicated that ACC had a more appropriate tone relative to HCC, W = 18818.0, p <0.001. The IG and X results were non-significant (see Table 2). Thus, *H03 is supported for FB only: ACC has a more appropriate tone relative to HCC on FB but not on IG or X.*

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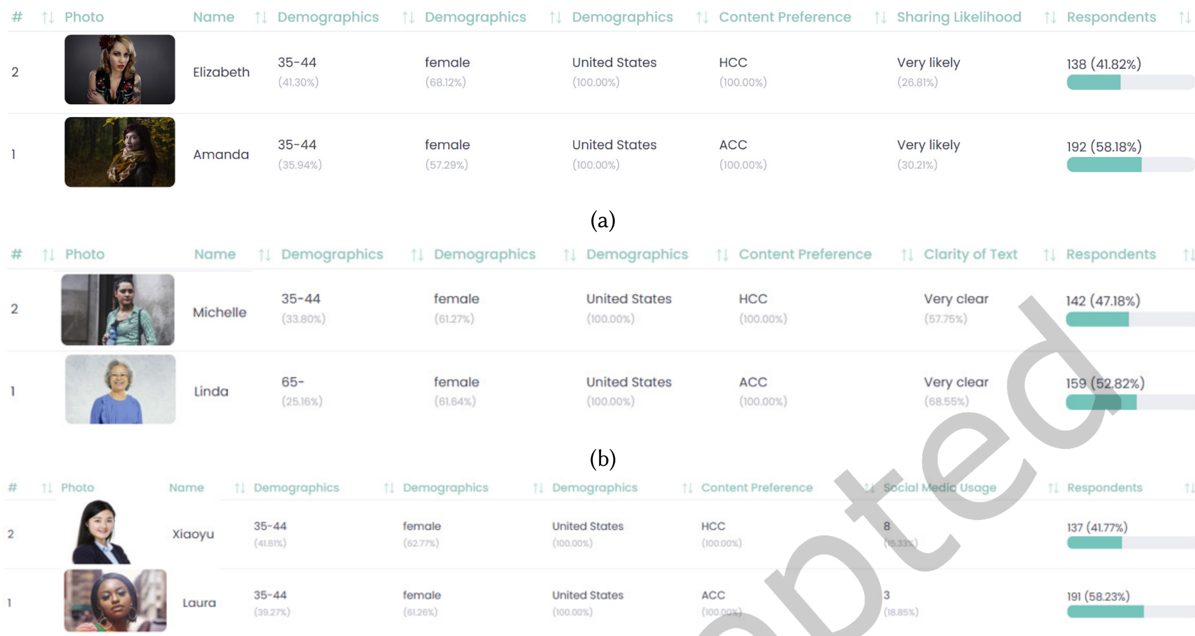

| # | Photo | Name | Demographics | Demographics | Demographics | Content Preference | Sharing Likelihood | Respondents |
|---|---|---|---|---|---|---|---|---|
| 2 | | Elizabeth | 35-44 (41.30%) | female (68.12%) | United States (100.00%) | HCC (100.00%) | Very likely (26.81%) | 138 (41.82%) |
| 1 | | Amanda | 35-44 (35.94%) | female (57.29%) | United States (100.00%) | ACC (100.00%) | Very likely (30.21%) | 192 (58.18%) |

(a)

| # | Photo | Name | Demographics | Demographics | Demographics | Content Preference | Clarity of Text | Respondents |
|---|---|---|---|---|---|---|---|---|
| 2 | | Michelle | 35-44 (33.80%) | female (61.27%) | United States (100.00%) | HCC (100.00%) | Very clear (57.75%) | 142 (47.18%) |
| 1 | | Linda | 65- (25.16%) | female (61.64%) | United States (100.00%) | ACC (100.00%) | Very clear (68.55%) | 159 (52.82%) |

(b)

| # | Photo | Name | Demographics | Demographics | Demographics | Content Preference | Social Media Usage | Respondents |
|---|---|---|---|---|---|---|---|---|
| 2 | | Xiaoyu | 35-44 (41.61%) | female (62.77%) | United States (100.00%) | HCC (100.00%) | 8 (15.33%) | 137 (41.77%) |
| 1 | | Laura | 35-44 (39.27%) | female (61.26%) | United States (100.00%) | ACC (100.00%) | 3 (18.85%) | 191 (58.23%) |

(c)

Fig. 4. Set of personas based on preference for ACC or HCC by platform, FB, IG, or X, generated by Survey2Persona.

**H04: ACC has more effective calls to action (CTA) than HCC.** For FB, the ACC had a higher CTA score than HCC, W = 23572.5, p <0.001. For IG, ACC had a higher CTA score than HCC, W = 32135.5, p = 0.024. For X, ACC had a higher CTA score than HCC, W = 27260.0, p <0.001. Thus, *H04 is fully supported: ACC has more effective calls to action (CTA) than HCC for all platforms.*

## 4.2 RQ2: How do emotional responses elicited by ACC differ from those elicited by HCC?

Table 2 shows the Wilcoxon test results of the emotions measure.

**H05. ACC has stronger positive emotional responses from users than HCC.** For FB, a Wilcoxon signed-rank test indicated that ACC had higher emotional response scores than HCC, W = 17605.0, p = 0.008. For IG, ACC had higher emotional response scores than HCC, W = 15878.0, p = 0.002. The result for X was non-significant. Thus, *H05 is supported for FB and IG: ACC has stronger positive emotional responses from users than HCC on FB and IG but not on X.*

## 4.3 RQ3: How does user engagement with ACC differ from engagement with HCC?

A Wilcoxon signed-rank test was conducted to compare HCC and ACC on FB, IG, and X regarding engagement measures. The results are summarized in Table 2.

**H06: ACC results in more reads than HCC.** For FB, ACC had higher reads than HCC, W = 20374.5, p = 0.001. The IG and X results were non-significant (see Table 2). Thus, *H06 is supported for FB only: ACC results in more reads than HCC on FB but not on IG or X.*

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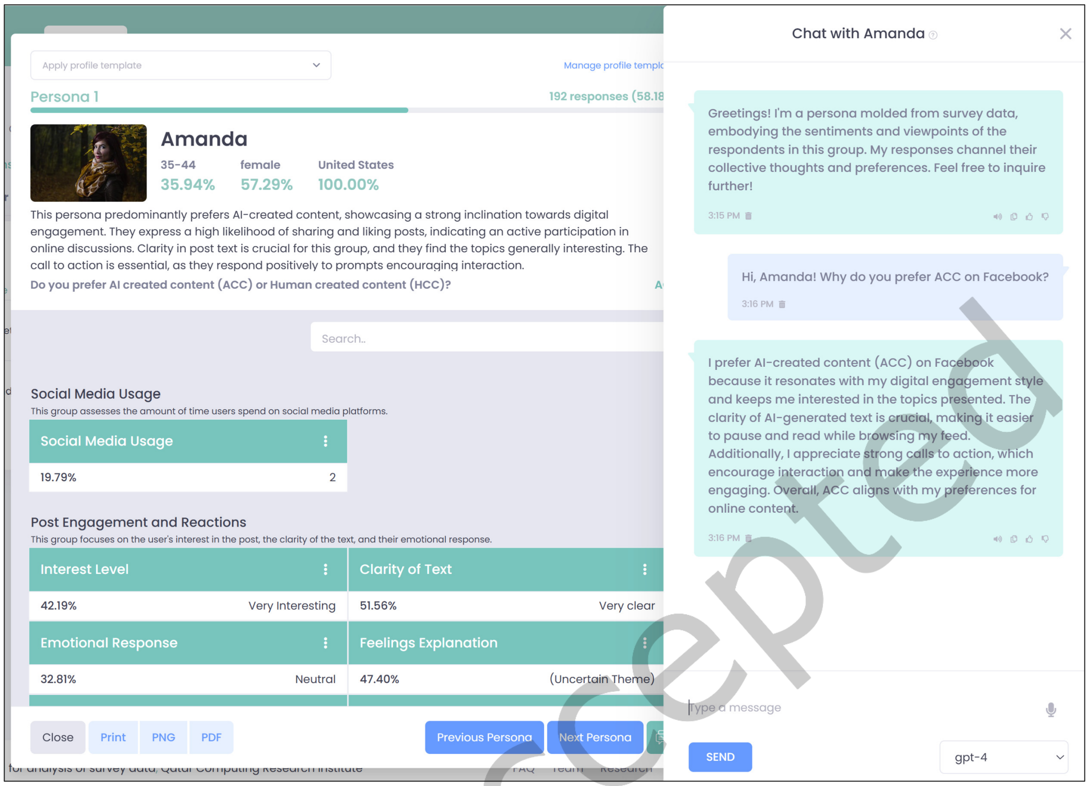


Fig. 5. Example of a Survey2Person Persona Engaged in Dialogue Mode.

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**H07: ACC results in more views than HCC.** For FB, ACC had a higher views score than HCC, W = 23083.0, p = 0.014. The IG and X results were non-significant (see Table 2). Thus, *H07 is supported for FB only: ACC results in more views than HCC on FB but not on IG or X.*

**H08: ACC results in more likes than HCC.** For FB, ACC had a higher likes score than HCC, W = 20405.0, p <0.001. The IG and X results were non-significant (see Table 2). Thus, *H08 is supported for FB only: ACC results in more likes than HCC on FB but not on IG or X.*

**H09: ACC generates more comments than HCC.** For FB, ACC had a higher comments score than HCC, W = 19613.0, p = 0.005. For X, ACC had a higher comments score than HCC, W = 20274.0, p = 0.028. The IG result was non-significant (see Table 2). Thus, *H09 is supported for FB and X only: ACC generates more comments than HCC on FB and X but not on IG.*

**H10: ACC will be shared more frequently than HCC** For FB, ACC had a higher share score than HCC, W = 18200.5, p <0.001. The IG and X results were non-significant (see Table 2). Thus, *H10 is supported for FB only: ACC will be shared more frequently than HCC on FB but not on IG or X.*

## 4.4 RQ4: Do users prefer ACC or HCC?

**H11: Users will exhibit a greater preference for ACC than for HCC.** The Chi-square test of independence was performed to test the preference for ACC relative to HCC among participants on FB, IG, and X. FB users had a higher preference for ACC, $\chi^2(1, N = 903) = 35.48$, p <.001. The ACC (n = 541) was preferred more frequently

Table 2. Wilcoxon test results comparing HCC with ACC across different measures and platforms. Includes medians (Md), Wilcoxon statistic (W), p-values (p), sample size (N), Z-statistics (Z), and effect size (r). Significant results are highlighted in green.

| Platform | RQ | Measure | Md (HCC) | Md (ACC) | W | p | N | Z | r |
|---|---|---|---|---|---|---|---|---|---|
| FB | RQ01 | Topical (H01) | 4.0 | 4.0 | **20701.0** | 0.001 | 902 | 3.323 | 0.111 |
| | | Clarity (H02) | 5.0 | 5.0 | **17957.0** | <0.0001 | 902 | 5.062 | 0.168 |
| | | Tone (H03) | 4.0 | 4.0 | **18818.0** | <0.0001 | 902 | 6.607 | 0.220 |
| | | CTA (H04) | 4.0 | 4.0 | **23572.5** | <0.0001 | 902 | 6.234 | 0.207 |
| | RQ02 | Emotions (H05) | 3.0 | 4.0 | **17605.0** | 0.008 | 902 | 2.639 | 0.088 |
| | RQ03 | Read (H06) | 4.0 | 4.0 | **20374.5** | 0.001 | 902 | 3.237 | 0.108 |
| | | View (H07) | 4.0 | 4.0 | **23083.0** | 0.014 | 902 | 2.460 | 0.082 |
| | | Like (H08) | 4.0 | 4.0 | **20405.0** | <0.0001 | 902 | 4.300 | 0.143 |
| | | Comment (H09) | 3.0 | 3.0 | **19613.0** | 0.005 | 902 | 2.802 | 0.093 |
| | | Share (H10) | 3.0 | 4.0 | **18200.5** | <0.0001 | 902 | 4.269 | 0.142 |
| IG | RQ01 | Topical (H01) | 4.0 | 4.0 | 18521.5 | 0.720 | 914 | 0.358 | 0.012 |
| | | Clarity (H02) | 5.0 | 5.0 | 20424.0 | 0.266 | 914 | 1.113 | 0.037 |
| | | Tone (H03) | 4.0 | 4.0 | 26310.5 | 0.203 | 914 | 1.274 | 0.042 |
| | | CTA (H04) | 4.0 | 4.0 | **32135.5** | 0.024 | 914 | 2.250 | 0.074 |
| | RQ02 | Emotions (H05) | 3.0 | 4.0 | **15878.0** | 0.002 | 914 | 3.136 | 0.104 |
| | RQ03 | Read (H06) | 4.0 | 4.0 | 21309.5 | 0.435 | 914 | 0.780 | 0.026 |
| | | View (H07) | 4.0 | 4.0 | 24257.0 | 0.197 | 914 | 1.289 | 0.043 |
| | | Like (H08) | 4.0 | 4.0 | 24359.0 | 0.347 | 914 | 0.941 | 0.031 |
| | | Comment (H09) | 4.0 | 4.0 | 17612.0 | 0.574 | 914 | 0.562 | 0.019 |
| | | Share (H10) | 4.0 | 4.0 | 19156.5 | 0.259 | 914 | 1.128 | 0.037 |
| X | RQ01 | Topical (H01) | 4.0 | 4.0 | 21645.0 | 0.149 | 857 | 1.443 | 0.049 |
| | | Clarity (H02) | 5.0 | 5.0 | 21312.0 | 0.094 | 857 | 1.673 | 0.057 |
| | | Tone (H03) | 4.0 | 4.0 | 31205.5 | 0.258 | 857 | 1.130 | 0.039 |
| | | CTA (H04) | 4.0 | 4.0 | **27260.0** | <0.000 | 857 | 4.782 | 0.163 |
| | RQ02 | Emotions (H05) | 4.0 | 4.0 | 23858.0 | 0.146 | 857 | 1.454 | 0.050 |
| | RQ03 | Read (H06) | 4.0 | 4.0 | 22128.5 | 0.090 | 857 | 1.697 | 0.058 |
| | | View (H07) | 4.0 | 4.0 | 22657.0 | 0.576 | 857 | 0.559 | 0.019 |
| | | Like (H08) | 4.0 | 4.0 | 27759.5 | 0.070 | 857 | 1.815 | 0.062 |
| | | Comment (H09) | 4.0 | 4.0 | **20274.0** | 0.028 | 857 | 2.199 | 0.075 |
| | | Share (H10) | 4.0 | 4.0 | 20693.5 | 0.072 | 857 | 1.799 | 0.061 |

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than HCC (n = 362). X users had a higher preference for ACC, $\chi^2$ (1, N = 858) = 12.61, p <.001. The ACC (n = 481) was preferred more frequently than HCC (n = 377). The result on IG was non-significant. Thus, *H11 is supported for FB and X only: ACC is preferred to HCC on FB and X but not on IG.*

Table 3 summarizes the results of the hypothesis testing.

## 4.5 RQ5: How do personas of users who prefer ACC compare with users who prefer HCC?

Based on a binary persona generation (i.e., ACC and HCC), a person for each archetype preference was created, with the representative demographic being the most commonly occurring from survey respondents (with the

Table 3. Support level for each hypothesis based on the study results.

| Hypothesis | Fully Supported | Partially Supported | Not Supported |
|---|---|---|---|
| H01: ACC has greater topical relevance than HCC | | ✓(FB) | |
| H02: ACC has superior clarity compared to HCC | | ✓(FB) | |
| H03: ACC has a more appropriate tone relative to HCC | | ✓(FB) | |
| H04: ACC has more effective calls to action (CTA) than HCC | ✓(FB, IG, X) | | |
| H05: ACC has stronger positive emotional responses from users than HCC | | ✓(FB, IG) | |
| H06: ACC results in more reads than HCC | | ✓(FB) | |
| H07: ACC results in more views than HCC | | ✓(FB) | |
| H08: ACC results in more likes than HCC | | ✓(FB) | |
| H09: ACC generates more comments than HCC | | ✓(FB, X) | |
| H10: ACC will be shared more frequently than HCC | | ✓(FB) | |
| H11: Users will exhibit a greater preference for ACC than for HCC | | ✓(FB, X) | |

associated percentages), as per established persona development practices [12]. This approach corresponds to the concept of using "extreme personas" to tease out differences between user segments at an opposing end of a spectrum [110]. For this, we applied *S2P*, a state-of-the-art interactive persona system [52] to automatically generate persona descriptions based on the corresponding survey responses for each segment [57]. Each persona corresponded to one of the six possible user segments derived from content preference (n=2) and platforms (n=3) (see Table 4). To uncover the underlying reasons for content preference, we posed a uniform question to each persona: *"Why do you prefer ACC/HCC on FB/IN/X?"*. The collected responses, based on S2P's interpretation of the personas' underlying data, are summarized in Table 5.

From the persona responses in Table 5, it appears that the main reasons for preferring ACC or HCC relate to emotional or cognitive reactions to the content based on individual preferences. The persona responses also reveal platform-specific trends in content preferences, highlighting differences in UE and perception of ACC versus HCC. For FB and IG, clarity and engagement are key drivers of content preference, with HCC respondents valuing authenticity and emotional connection, while ACC respondents focusing on strong CTA and readability. On X, HCC users emphasize authenticity and personal expression, whereas ACC respondents prioritize clarity, neutrality, and structured content. This suggests that the preference drivers for ACC are clarity and engagement-oriented and for HCC are emotional depth and relatability. These findings indicate that content strategy optimization must be based on both platform dynamics and audience content expectations.

## 5 Discussion

### 5.1 Answering the RQs

Addressing RQ1, ACC exhibited greater adaptability for FB, outperforming HCC in terms of clarity, tone, and topical interest. This suggests that GPT-4 effectively aligns with FB's content dynamics, out of reasons that require further research. For IG and X, the advantages of ACC were less pronounced, with most differences between ACC and HCC being non-significant. This indicates that while LLMs can effectively tailor content for given platforms, its effect varies by the platform.

Addressing RQ2, ACC elicited stronger positive emotional responses than HCC on FB and IG. This finding indicates that GPT-4 can create content that resonates emotionally with users. However, for X, no significant

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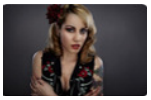
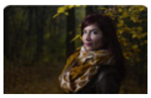
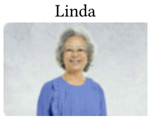
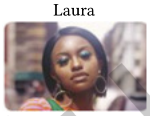
Table 4. Descriptive Data of Survey2Persona Personas.

| Platform | Persona | Age (%) | Gender (%) | Description |
|---|---|---|---|---|
| FB | Elizabeth  | 35-44 (41.30%) | Female (68.12%) | This persona exhibits a strong preference for content created by humans over AI-generated options. The majority finds the topics presented to be very interesting, indicating a desire for engaging and thought-provoking material. They are likely to pause and read posts in their social media feeds, reflecting a higher engagement level. Although they express a range of likelihoods to share or comment, many still show a willingness to interact with content. Overall, this group values clarity and quality in writing, reinforcing the importance of human touch in content creation. |
| FB | Amanda  | 35-44 (35.94%) | Female (57.29) | This persona predominantly prefers AI-created content, showcasing a strong inclination towards digital engagement. They express a high likelihood of sharing and liking posts, indicating an active participation in online discussions. Clarity in post text is crucial for this group, and they find the topics generally interesting. The CTA is essential, as they respond positively to prompts encouraging interaction. |
| IG | Michelle  | 35-44 (33.80%) | Female (61.27%) | This persona shows a strong preference for human-created content, valuing clarity and quality in writing. They find the topic of posts very interesting and are likely to engage through likes and comments. The CTA in posts resonates well, encouraging viewers to participate actively. Additionally, their social media habits suggest they spend a moderate amount of time engaging with content, reflecting a desire for meaningful interactions. |
| IG | Linda  | 65_ (25.26%) | Female (61.64%) | This persona exhibits a strong preference for AI-generated content, indicating a clear favor for technology-driven communication. The majority finds the text of the posts to be very clear, and they are likely to engage with the content by viewing and sharing it. Topics of interest resonate well with this group, leading to a positive perception of the overall quality and tone of the writing. Additionally, they appreciate a strong CTA, enhancing their likelihood of interacting with the posts. |
| X | Xiaoyu  | 35-44 (41.61%) | Female (62.77%) | This persona strongly prefers human-created content over AI-generated alternatives, reflecting a deep appreciation for authenticity. They engage with social media actively, often spending several hours daily on various platforms. This group is likely to view posts, finding the topics very interesting, and they respond positively to clear and high-quality writing. Their inclination to interact with posts is evident, as they frequently show interest in commenting and sharing content with others. |
| X | Laura  | 35-44 (39.27%) | Female (61.26) | This persona is primarily inclined towards AI-generated content, demonstrating a strong preference for digital interactions. They tend to spend a significant amount of time on social media, showing a high likelihood of engaging with posts through shares and comments. Clarity and quality in content are paramount for them, as they favor well-written and clear posts. Their interest in topics is notably high, often finding them very interesting, which drives their interaction levels. Overall, this group is characterized by their eagerness to engage with and share content that resonates with them. |

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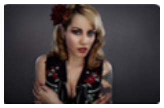
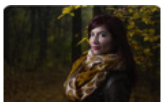
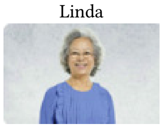
differences in emotional response were observed between ACC and HCC, implying that ACC does not necessarily evoke stronger emotions in the fast-paced, text-centric environment of X.

Addressing RQ3, ACC on FB consistently outperformed HCC in higher UE across multiple metrics, including reads, views, likes, comments, and shares. However, for IG and X, the impact of AI on engagement was less conclusive, with most engagement metrics showing no significant differences between ACC and HCC. Again, this repeats the observation from RQ1 in that the effects of LLMs are to some extent platform specific.

Table 5. Chat responses from personas on reasons for ACC or HCC preferences.

| Platform | Persona | Preference | Dialogue Response |
|---|---|---|---|
| FB | Elizabeth  | HCC | Hi there! I prefer human-created content (HCC) on Facebook because it resonates more with me and feels more engaging and authentic. It's important to me that the posts I encounter are interesting and thought-provoking, which I find is often the case with HCC. Additionally, I am very likely to pause and read posts that catch my eye, and I appreciate the clarity and quality that typically come with human writing. Overall, HCC provides a richer experience on social media. |
| FB | Amanda  | ACC | I prefer AI-created content (ACC) on Facebook because it resonates with my digital engagement style and keeps me interested in the topics presented. The clarity of AI-generated text is crucial, making it easier to pause and read while browsing my feed. Additionally, I appreciate strong calls to action, which encourage interaction and make the experience more engaging. Overall, ACC aligns with my preferences for online content. |
| IG | Michelle  | HCC | Hi there! I prefer human-created content on Instagram because it tends to offer better clarity and quality in writing, which I really value. Engaging with content that has a strong call to action resonates with me, encouraging meaningful interactions. Overall, human-created posts feel more relatable and engaging, making my time spent on social media more enjoyable. |
| IG | Linda  | ACC | I prefer AI-created content (ACC) on Instagram because it tends to be very clear and resonates well with me. The technology-driven communication feels fresh, and I appreciate the strong call to action that encourages engagement. This content often prompts me to pause and read while browsing, making my social media experience more enjoyable. Overall, I find that ACC enhances my interactions on platforms like Instagram. |
| X | Xiaoyu  | HCC | I prefer human-created content (HCC) because it resonates with my appreciation for authenticity and the unique perspectives that come from personal experiences. I find HCC to be more engaging and relatable, which enhances my overall interaction with the content. Additionally, I believe that human touch in writing adds depth and emotional connection that AI-generated content often lacks. |
| X | Laura  | ACC | I prefer AI-created content (ACC) because it consistently delivers clarity and quality, which are crucial for my engagement. With 100% of my group favoring ACC, we find that it resonates well with our interests. Additionally, AI-generated content often maintains a neutral to somewhat formal tone, which suits our preferences and encourages thoughtful interactions. Overall, the clarity in the content makes it much easier for us to connect and engage with the posts. |

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Addressing RQ4, users preferred ACC over HCC on FB and X. This finding indicates that ACC may align more closely with user expectations and engagement behaviors on these platforms. However, for IG, users did not indicate a significant preference between ACC and HCC. Overall, these findings point to the same direction as those from the previous RQs in that LLMs content is generally preferred.

Concerning RQ5, clarity, emotional appeal, and CTA were contributing factors in users preferring ACC or HCC, indicating that these factors play a role in users' formation of online content preference, as one would logically assume.

In summary, our findings indicate that GPT-4 creates cross-platform content that is preferred over HCC on FB and X, while demonstrating a user preference comparable, but not preferred more, to that of HCC on IG. This finding underscores the evolving capabilities of LLMs [19], which can adapt to diverse social media environments, even when each are characterized by distinct content formats and audience engagement dynamics. For FB, all tested hypotheses yielded significant results, (i.e., participants perceived ACC as more effectively compared to HCC). This was reflected in key aspects such as topical relevance, clarity, tone, and CTA. These findings suggest that ACC aligns well with FB's content dynamics and UE patterns.

Our findings show that ACC holds a distinct advantage in evoking emotional responses on FB and IG, whereas on X, HCC maintains a competitive edge. This discrepancy may be influenced by the nature of the content, as our study focused on news-related posts, which have been shown to elicit varying emotional responses across different social media platforms [9]. Additionally, FB's platform design, which includes five distinct reaction icons—love, surprise, joy, sadness, and anger—allows for a more nuanced expression of emotional engagement, potentially amplifying the observed effect of ACC. This suggests that platform-specific features influence how users interact emotionally with content, which may also have implications for training LLMs like GPT-4 to generate more emotionally resonant and platform-adapted content.

On FB, ACC consistently outperformed HCC across all UE metrics. The largest differences were observed in Likes and Shares, suggesting that ACC may be more likable and shareable on FB compared to HCC. On X, ACC encouraged more comments than HCC, while other engagement metrics—including reads, views, likes, and shares—showed no significant differences. This aligns with prior findings that different types of content perform better on different platforms [8]. Given that FB favors narrative-driven content, ACC may be naturally more suited to FB's content preferences, resulting in higher engagement. Conversely, on X, where concise and real-time content is prioritized, ACC appears to perform similar to HCC.

The CTA is where ACC consistently outperforms HCC across FB, IG, and X. ACC proves to be more effective in prompting user interaction and encouraging engagement through well-structured CTAs, whereas HCC often lacks explicit engagement prompts. For example, in a single video post, ACC-generated CTAs varied by platform: FB: *"We invite you to share your thoughts on the narratives that shape our world."* IG: *"Don't forget to leave a comment and let us know which artifact you'd like us to explore next!"* X: *"Join us as we explore the captivating yet controversial history behind these artifacts."* In contrast, HCC for the same video did not include any form of CTA, reinforcing LLMs' advantage in strategically incorporating prompts that drive user interaction and engagement.

Notably, we did not explicitly instruct GPT-4 to include CTA statements, yet most ACC automatically incorporated them. This suggests that GPT-4 inherently recognizes the importance of CTAs in digital engagement. One possible explanation is that GPT-4 has been trained on extensive text data, including successful social media posts, marketing materials, and other promotional content that frequently utilize CTAs. Given that CTAs are known to enhance UE with social media posts [82], the model appears to have internalized their strategic use as a best practice. Furthermore, including CTAs without explicit prompting indicates that GPT-4 autonomously applies learned principles of effective content marketing. This suggests that LLMs can adaptively generate content that aligns with engagement-driven communication strategies, even when not directly instructed to do so.

Additionally, while CTA usage is more pronounced in ACC across all three platforms, engagement metrics on IG and X do not show significant differences compared to HCC, except for higher comment activity on X. This discrepancy may stem from various audience-related factors identified in prior research, particularly the pre-existing relationship between the audience and the content creator[82]. For instance, on IG, a CTA is more likely to encourage engagement from existing followers through electronic word-of-mouth (eWOM) but has a limited impact on non-followers[82]. This suggests that while AI-generated CTAs are strategically well-formed, their effectiveness in driving engagement may depend on platform-specific audience dynamics and user familiarity with the content source.

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### 5.2 Theoretical Implications

A key implication of our findings is that AI tools can effectively scale social media strategies, enabling broader reach and higher engagement without proportional increases in effort or resources. Our results demonstrate that ACC drives greater UE and incorporates more effective CTAs, reinforcing the potential of LLMs to optimize content marketing. This research highlights that LLMs, such as GPT-4, can generate content that adapts to diverse social media platforms, often matching or surpassing HCC in key areas such as platform adaptability, emotional engagement, user interaction, and content preference–critical factors in effectively connecting with social media audiences [34]. These findings suggest that LLMs exhibit a high degree of linguistic flexibility and creative adaptability, positioning them as valuable assets for scalable and impactful content creation across various digital platforms.

This research demonstrates that user responses to ACC vary by platform, with ACC outperforming HCC on FB and X, but showing less advantage on IG. These findings suggest that platform-specific characteristics—such as content length, format, tone, and visual emphasis—significantly shape how users perceive and engage with social media content, reinforcing the need for tailored ACC strategies. Additionally, ACC offers the advantage of maintaining a consistent quality and tone across posts and platforms, a crucial factor for brand identity and content uniformity [19]. This consistency is key in establishing a recognizable and trustworthy brand image, particularly when multiple content creators collaborate on cross-platform content strategies for different social media platforms.

This research emphasizes several ethical and social considerations associated with the use of ACC, particularly regarding authenticity, credibility, and accountability in digital communication. The increasing reliance on AI for content creation raises critical questions about transparency in authorship, the potential for misinformation, and the accountability of AI-generated outputs. These concerns underscore the need for further research into the ethical and societal implications of ACC [71, 85].

### 5.3 Practical Implications

Our findings indicate that ACC can serve as a valuable tool for content creators, particularly in enhancing and streamlining cross-platform content creation. Leveraging LLMs can help creators increase efficiency and maintain UE consistency across multiple platforms, making AI an effective complement to traditional content creation methods. Additionally, AI-driven content generation can reduce costs associated with human content creation, offering a cost-effective solution for small businesses and individual creators with limited budgets. This affordability makes ACC an attractive option for scaling digital marketing efforts.

However, despite these advantages, human oversight remains crucial to ensure that ACC maintains accuracy, contextual relevance, and ethical integrity [35]. Even though LLMs is efficient, its outputs may still require refinement and validation to align with an organization’s strategic communication goals and ethical standards [16]. Integrating AI’s content generation capabilities with human editorial oversight may provide the most effective and responsible strategy for leveraging LLMs in content creation.

This research highlights potential challenges for content consumers when engaging with ACC. These challenges include difficulty in distinguishing ACC from HCC, the risk of manipulation or deception, and the potential erosion of human connection and trust with content and its creators [4, 33]. These findings suggest that content consumers must become more aware and critical of the digital content they engage with. The increasing prevalence of ACC requires the development of digital literacy and media literacy skills to help users evaluate content authenticity, recognize LLM-created content, and critically assess the reliability of online information [105].

This research presents new opportunities for social media research, including examining the effects of ACC on user behavior, attitudes, and cognition, comparing the performance of different LLMs in cross-platform content generation, and developing methods and metrics to assess and improve the quality and effectiveness of ACC.

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These findings suggest that ACC can serve as both a research topic and a methodological tool, offering novel insights into digital engagement, content personalization, and platform-specific optimization strategies.

Our study demonstrates that LLMs can adapt content characteristics to different social media platforms, allowing content creators to produce consistent and platform-specific content efficiently. ACC is also capable of eliciting emotional engagement, sometimes exceeding HCC in emotional resonance. However, it remains essential for creators to ensure alignment between ACC and their organization's messaging and values. The effectiveness of HCC varies across platforms, emphasizing the need for platform-specific adjustments to optimize engagement. Regardless of whether content is LLMs- or human-created, it must maintain high quality, authenticity, and relevance to effectively engage users [1].

As AI continues to shape content creation, it is crucial to prioritize ethical and legal considerations to mitigate risks such as biases, misinformation, and a lack of transparency. Ensuring responsible AI use in digital media requires clear guidelines, oversight mechanisms, and platform accountability to maintain content integrity. Looking ahead, these insights can inform the development of AI-driven systems that enable content creators to effortlessly generate cross-platform content from any text input.

## 6 Limitations and Future Work

While our study provides valuable insights, it also has limitations.

First, our participant pool was primarily U.S.-based, which may not fully capture diverse global perspectives on ACC versus HCC. Cultural differences can influence content perception, emotional engagement, and platform preferences, and given that LLMs are predominantly trained on Western datasets, their adaptability to non-Western linguistic and cultural contexts remains an open question. Additionally, our study focused on content from a single organization that cross-posts on FB, IG, and X, whereas different organizations may use a broader range of platforms. To develop a more comprehensive understanding of LLMs adaptability, future research should include a wider set of user groups outside the U.S. and examine additional platforms, such as YouTube, LinkedIn, and TikTok, to evaluate ACC across varied content formats and engagement models.

This study used a combined prompt to create cross-platform content from one input. However, future research could explore the effects of using separate prompts for each platform. A comparative analysis of single versus combined prompting, using the method applied here, could provide deeper insights into the effectiveness of different prompting strategies for optimizing platform-specific content. While LLMs inherently encode platform-specific characteristics, relying solely on platform names in prompts may introduce biases in generated outputs. A potential alternative is to incorporate real-world examples and user profiles specific to each platform, which could help reduce biases and enhance contextual relevance. Future research could evaluate this alternative prompting approach to determine its effectiveness in producing more authentic and tailored content for diverse social media platforms.

Additionally, this study relied exclusively on video content transcripts to generate social media posts. While this approach is well-suited for video-based content, it does not account for other common social media formats, such as IG photo albums, standalone photo captions, or images with overlaid text. Future research should address these limitations by expanding the scope to additional content types and evaluating how ACC performs across diverse media formats.

This study required participants to carefully read and evaluate social media content, whereas in real-world settings, users often scan posts quickly rather than engaging in detailed reading. This difference in attention duration may impact how our findings translate to actual social media interactions. A potential direction for future research is to conduct real-world experiments by posting ACC and HCC on an organization's live social media accounts. This could involve creating two versions of a post with slight variations and measuring organic UE metrics such as views, likes, comments, and shares.

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The findings may have been partially influenced by differences in post length, as ACC tended to be longer than HCC. This length discrepancy could have affected participant evaluations, particularly on platforms where brevity is a key characteristic. A notable trend in our results suggests that LLMs' impact is less pronounced for shorter social media posts, such as those on X and IG. This aligns with prior research indicating that content length influences user perception and engagement [29, 30, 39]. Future research could further explore how post length affects ACC evaluations, particularly by controlling for length variations between ACC and HCC, to isolate the effects of AI-driven content creation from those of post length itself.

Previous studies indicate that GPT-4 can tailor content to specific target audiences, but it may exhibit biases against minority populations due to imbalanced training data [102]. This limitation suggests that ACC may not always be equally effective across diverse audience segments. To enhance GPT-4's performance in generating more engaging ACC for platforms like X and IG, future research could explore incorporating high-engagement posts from these platforms as exemplars in the prompt. Additionally, including audience demographic details when prompting GPT-4 could potentially improve targeted content generation, ensuring that AI-created posts resonate more effectively with specific user groups. This targeted prompting approach presents an intriguing direction for future research. However, implementing and testing AI-generated posts on live social media platforms would require additional effort, including real-time engagement tracking, platform-specific optimizations, and iterative refinements based on audience response patterns.

In this study, we used GPT-4 to generate social media content. However, future research could benefit from exploring and evaluating the performance of alternative LLMs, such as Gemini, Cohere, and Claude. Comparing multiple LLMs would provide insights into how different models handle cross-platform content generation, engagement optimization, and platform-specific customization. In addition, such studies could help identify which models produce the most effective and contextually relevant content for various social media platforms.

## 7 Conclusion

This research examined the effectiveness of OpenAI's GPT-4 in generating cross-platform content for FB, IG, and X. Through a user study, participants evaluated ACC versus HCC across multiple dimensions, including platform adaptability, emotional response, engagement, and user preference. The results revealed that ACC was highly preferred over HCC on FB and X, while preferences on IG remained similar between ACC and HCC. The CTA emerged as the strongest feature of ACC across all platforms, whereas tone was identified as the weakest aspect. Additionally, ACC elicited stronger positive emotional responses than HCC on FB and IG, though this effect was not observed on X. These findings suggest that LLMs like GPT-4 have the potential to transform social media content creation, particularly for cross-platform posting by enhancing efficiency, expanding reach, and increasing engagement. However, they also underscore the need for ongoing improvements and evaluations to ensure that LLMs are used ethically and responsibly in social media content generation.

## 8 DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author(s) used Open AI's ChatGPT (GPT-3.5 and GPT-4) to assist us in the analysis and provide material for addressing the 'blank page' problem in writing. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

## References

[1] Eugene Agichtein, Carlos Castillo, Debora Donato, Aristides Gionis, and Gilad Mishne. 2008. Finding high-quality content in social media. In *Proceedings of the 2008 International Conference on Web Search and Data Mining (WSDM '08)*. Association for Computing Machinery, New York, NY, USA, 183–194. doi:10.1145/1341531.1341557

Just Accepted

[2] Mohammad Awad AlAfnan and Siti Fatimah MohdZuki. 2023. Do artificial intelligence chatbots have a writing style? An investigation into the stylistic features of ChatGPT-4. *Journal of Artificial intelligence and technology* 3, 3 (2023), 85–94.

[3] Maeghin Alarid. 2016. Recruitment and radicalization: The role of social media and new technology. *Impunity: Countering illicit power in war and transition* (2016), 313–330.

[4] Kholoud Aldous, Joni Salminen, Ali Farooq, Soon-gyo Jung, and Bernard Jansen. 2024. Using ChatGPT in content marketing: enhancing users' social media engagement in cross-platform content creation through generative AI. In *Proceedings of the 35th ACM Conference on Hypertext and Social Media*. 376–383.

[5] Kholoud Khalil Aldous, Jisun An, and Bernard J. Jansen. 2019. The Challenges of Creating Engaging Content: Results from a Focus Group Study of a Popular News Media Organization. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems (CHI EA '19)*. Association for Computing Machinery, New York, NY, USA, 1–6. doi:10.1145/3290607.3312810

[6] Kholoud Khalil Aldous, Jisun An, and Bernard J. Jansen. 2019. Predicting Audience Engagement Across Social Media Platforms in the News Domain. In *Social Informatics (Lecture Notes in Computer Science)*. Springer International Publishing, Cham, 173–187. doi:10.1007/978-3-030-34971-4_12

[7] Kholoud Khalil Aldous, Jisun An, and Bernard J Jansen. 2019. Stylistic features usage: Similarities and differences using multiple social networks. In *Social Informatics: 11th International Conference, SocInfo 2019, Doha, Qatar, November 18–21, 2019, Proceedings 11*. Springer, 309–318.

[8] Kholoud Khalil Aldous, Jisun An, and Bernard J Jansen. 2019. View, like, comment, post: Analyzing user engagement by topic at 4 levels across 5 social media platforms for 53 news organizations. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 13. 47–57.

[9] Kholoud Khalil Aldous, Jisun An, and Bernard J. Jansen. 2022. Measuring 9 Emotions of News Posts from 8 News Organizations across 4 Social Media Platforms for 8 Months. *Trans. Soc. Comput.* 4, 4, Article 15 (mar 2022), 31 pages. doi:10.1145/3516491

[10] Kholoud Khalil Aldous, Jisun An, and Bernard J. Jansen. 2023. What really matters?: characterising and predicting user engagement of news postings using multiple platforms, sentiments and topics. *Behaviour & Information Technology* 42, 5 (April 2023), 545–568. doi:10.1080/0144929X.2022.2030798

[11] Mostafa M. Amin, Erik Cambria, and Björn W. Schuller. 2023. Will Affective Computing Emerge From Foundation Models and General Artificial Intelligence? A First Evaluation of ChatGPT. 38, 2 (2023), 15–23. Publisher: IEEE.

[12] Jisun An, Haewoon Kwak, Soon-gyo Jung, Joni Salminen, M Admad, and B Jansen. 2018. Imaginary people representing real numbers: Generating personas from online social media data. *ACM Transactions on the Web (TWEB)* 12, 4 (2018), 1–26.

[13] Jisun An and Ingmar Weber. 2018. Diversity in online advertising: a case study of 69 brands on social media. In *Social Informatics: 10th International Conference, SocInfo 2018, St. Petersburg, Russia, September 25-28, 2018, Proceedings, Part I 10*. Springer, 38–53.

[14] Simon Attfield, Gabriella Kazai, Mounia Lalmas, and Benjamin Piwowarski. 2011. Towards a science of user engagement (position paper). In *WSDM workshop on user modelling for Web applications*. 9–12.

[15] Claus Atzenbeck, Sam Brooker, and Daniel Roßner. 2023. Storytelling Machines. In *Proceedings of the 6th Workshop on Human Factors in Hypertext* (Rome Italy, 2023-09-04). ACM, 1–9. doi:10.1145/3603607.3613481

[16] Lateef Ayinde, Muhamad Prabu Wibowo, Benhur Ravuri, and Forhan Bin Emdad. 2023. ChatGPT as an important tool in organizational management: A review of the literature. *Business Information Review* 40, 3 (2023), 137–149.

[17] Navid Ayoobi, Sadat Shahriar, and Arjun Mukherjee. 2023. The Looming Threat of Fake and LLM-generated LinkedIn Profiles: Challenges and Opportunities for Detection and Prevention. In *Proceedings of the 34th ACM Conference on Hypertext and Social Media* (Rome Italy, 2023-09-04). ACM, 1–10. doi:10.1145/3603163.3609064

[18] Fabrício Benevenuto, Tiago Rodrigues, Meeyoung Cha, and Virgílio Almeida. 2012. Characterizing user navigation and interactions in online social networks. *Information Sciences* 195 (2012), 1–24.

[19] Michael Bossetta and Rasmus Schmøkel. 2022. Cross-Platform Emotions and Audience Engagement in Social Media Political Campaigning: Comparing Candidates' Facebook and Instagram Images in the 2020 US Election. *Political Communication* 40 (2022), 48 – 68. doi:10.1080/10584609.2022.2128949

[20] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems* 33 (2020), 1877–1901.

[21] Jasper David Brüns and Martin Meißner. 2024. Do you create your content yourself? Using generative artificial intelligence for social media content creation diminishes perceived brand authenticity. *Journal of Retailing and Consumer Services* 79 (2024), 103790.

[22] Erik Cambria, Dipankar Das, Sivaji Bandyopadhyay, and Antonio Feraco. 2017. Affective Computing and Sentiment Analysis. In *A Practical Guide to Sentiment Analysis*. Springer International Publishing, Cham, 1–10. doi:10.1007/978-3-319-55394-8_1

[23] David Carneros-Prado, Laura Villa, Esperanza Johnson, Cosmin C Dobrescu, Alfonso Barragán, and Beatriz García-Martínez. 2023. Comparative Study of Large Language Models as Emotion and Sentiment Analysis Systems: A Case-Specific Analysis of GPT vs. IBM Watson. In *International Conference on Ubiquitous Computing and Ambient Intelligence*. Springer, 229–239.


Just Accepted

[24] Jesse Chandler, Cheskie Rosenzweig, Aaron J. Moss, Jonathan Robinson, and Leib Litman. 2019. Online panels in social science research: Expanding sampling methods beyond Mechanical Turk. *Behavior Research Methods* 51, 5 (Oct. 2019), 2022–2038. doi:10.3758/s13428-019-01273-7

[25] Deborah S Chung. 2008. Interactive features of online newspapers: Identifying patterns and predicting use of engaged readers. *Journal of Computer-Mediated Communication* 13, 3 (2008), 658–679.

[26] David De Cremer, Nicola Morini Bianzino, and Ben Falk. 2023. How Generative AI Could Disrupt Creative Work. (2023). https://hbr.org/2023/04/how-generative-ai-could-disrupt-creative-work Section: AI and machine learning.

[27] Alberto Dafonte-Gómez. 2018. News Media and the Emotional Public Sphere Audiences as Medium: Motivations and Emotions in News Sharing. *International Journal of Communication* 12 (2018), 20.

[28] Mariano de Rivero, Cristhiam Tirado, and Willy Ugarte. 2021. FormalStyler: GPT based Model for Formal Style Transfer based on Formality and Meaning Preservation.. In *KDIR*. 48–56.

[29] Qi Deng, Michael J. Hine, Shaobo Ji, and Yun Wang. 2021. Understanding consumer engagement with brand posts on social media: The effects of post linguistic styles. *Electronic Commerce Research and Applications* 48 (July 2021), 101068. doi:10.1016/j.elerap.2021.101068

[30] Qi Deng, Yun Wang, Michel Rod, and Shaobo Ji. 2021. Speak to head and heart: The effects of linguistic features on B2B brand engagement on social media. *Industrial Marketing Management* 99 (Nov. 2021), 1–15. doi:10.1016/j.indmarman.2021.09.005

[31] Weiping Ding, Mohamed Abdel-Basset, Hossam Hawash, and Ahmed M Ali. 2022. Explainability of artificial intelligence methods, applications and challenges: A comprehensive survey. *Information Sciences* 615 (2022), 238–292.

[32] Rebecca Dolan, Jodie Conduit, Catherine Frethey-Bentham, John Fahy, and Steve Goodman. 2019. Social media engagement behavior: A framework for engaging customers through social media content. *European Journal of Marketing* 53, 10 (Jan. 2019), 2213–2243. doi:10.1108/EJM-03-2017-0182

[33] Duo Du, Yanling Zhang, and Jiao Ge. 2023. Effect of AI generated content advertising on consumer engagement. In *International conference on human-computer interaction*. Springer, 121–129.

[34] Reham Shawky Ebrahim. 2020. The Role of Trust in Understanding the Impact of Social Media Marketing on Brand Equity and Brand Loyalty. *Journal of Relationship Marketing* 19 (2020), 287 – 308. doi:10.1080/15332667.2019.1705742

[35] N Editorials. 2023. Tools such as ChatGPT threaten transparent science; here are our ground rules for their use. *Nature* 613, 612 (2023), 10–1038.

[36] Moran Fan and Chunling Zhang. 2025. A study of consumer demand differentiation under different anchor personas in agricultural products content marketing. *Journal of Marketing Communications* (2025), 1–26.

[37] Ali Farooq, Laila Dahabiyeh, and Christian Maier. 2023. Social media discontinuation: A systematic literature review on drivers and inhibitors. *Telematics and Informatics* 77 (2023), 101924.

[38] Yunhe Feng, Pradhyumna Poralla, Swagatika Dash, Kaicheng Li, Vrushabh Desai, and Meikang Qiu. 2023. The Impact of ChatGPT on Streaming Media: A Crowdsourced and Data-Driven Analysis using Twitter and Reddit. In *2023 IEEE 9th Intl Conference on Big Data Security on Cloud (BigDataSecurity), IEEE Intl Conference on High Performance and Smart Computing, (HPSC) and IEEE Intl Conference on Intelligent Data and Security (IDS)*. 222–227. doi:10.1109/BigDataSecurity-HPSC-IDS58521.2023.00046

[39] Dimitris C Gkikas, Katerina Tzafilkou, Prokopis K Theodoridis, Aristogiannis Garmpis, and Marios C Gkikas. 2022. How do text characteristics impact user engagement in social media posts: Modeling content readability, length, and hashtags number in Facebook. *International Journal of Information Management Data Insights* 2, 1 (2022), 100067.

[40] Fateneh Golpayegani, Nanxi Chen, Nima Afraz, Eric Gyamfi, Abdollah Malekjafarian, Dominik Schäfer, and Christian Krupitzer. 2024. Adaptation in edge computing: a review on design principles and research challenges. *ACM Transactions on Autonomous and Adaptive Systems* 19, 3 (2024), 1–43.

[41] Anthony G. Greenwald. 1976. Within-subjects designs: To use or not to use? *Psychological Bulletin* 83, 2 (1976), 314–320. doi:10.1037/0033-2909.83.2.314

[42] Jeffrey T. Hancock, Kailyn Gee, Kevin Ciaccio, and Jennifer Mae-Hwah Lin. 2008. I'm Sad You'Re Sad: Emotional Contagion in CMC. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work (CSCW '08)*. ACM, 295–298.

[43] Paul Harrigan, Uwana Evers, Morgan Miles, and Timothy Daly. 2017. Customer engagement with tourism social media brands. *Tourism Management* 59 (2017), 597–609.

[44] Valerie Hase, Karin Boczek, and Michael Scharkow. 2023. Adapting to affordances and audiences? A cross-platform, multi-modal analysis of the platformization of news on Facebook, Instagram, TikTok, and Twitter. *Digital Journalism* 11, 8 (2023), 1499–1520.

[45] Angelica Lermann Henestrosa, Hannah Greving, and Joachim Kimmerle. 2023. Automated journalism: The effects of AI authorship and evaluative information on the perception of a science journalism article. *Computers in Human Behavior* 138 (2023), 107445.

[46] Tim Highfield and Tama Leaver. 2016. Instagrammatics and digital methods: studying visual social media, from selfies and GIFs to memes and emoji. *Communication Research and Practice* 2 (2016), 47 – 62. doi:10.1080/22041451.2016.1155332

[47] Sanne Hille and Piet Bakker. 2014. Engaging the social news user: Comments on news sites and Facebook. *Journalism Practice* 8, 5 (2014), 563–572.


Just Accepted

[48] Linda D. Hollebeek, Choukri Menidjel, Marko Sarstedt, Johan Jansson, and Sigitas Urbonavicius. 2024. Engaging consumers through artificially intelligent technologies: Systematic review, conceptual model, and further research. 41, 4 (2024), 880–898. doi:10.1002/mar.21957 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/mar.21957.

[49] Y. Linlin Huang, Kate Starbird, Mania Orand, Stephanie A. Stanek, and Heather T. Pedersen. 2015. Connected Through Crisis: Emotional Proximity and the Spread of Misinformation Online. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work (CSCW '15)*. ACM, 969–980.

[50] Carroll E. Izard. 1991. *The Psychology of Emotions*. Springer Science & Business Media.

[51] Roope Jaakonmäki, Oliver Müller, and Jan Vom Brocke. 2017. The impact of content, context, and creator on user engagement in social media marketing. In *Proceedings of the Annual Hawaii International Conference on System Sciences*, Vol. 50. IEEE Computer Society Press, 1152–1160.

[52] Arne Jansen, Nicky Sulmon, Maarten Van Mechelen, Bieke Zaman, Jeroen Vanattenhoven, and Dirk De Grooff. 2013. Beyond the familiar? Exploring extreme input in brainstorms. In *CHI'13 Extended Abstracts on Human Factors in Computing Systems*. 1347–1352.

[53] Bernard Jansen. 2009. Understanding User-Web Interactions via Web Analytics. *Synthesis Lectures on Information Concepts, Retrieval, and Services* 1 (2009), 1–102.

[54] Bernard J Jansen, Joni O Salminen, and Soon-gyo Jung. 2020. Data-driven personas for enhanced user understanding: Combining empathy with rationality for better insights to analytics. *Data and Information Management* 4, 1 (2020), 1–17.

[55] Mingxia Jia, Yuxiang Chris Zhao, Shijie Song, Xiaoyu Zhang, Dawei Wu, and Jinhao Li. 2024. How vicarious learning increases users' knowledge adoption in live streaming: The roles of parasocial interaction, social media affordances, and knowledge consensus. *Information Processing & Management* 61, 2 (2024), 103599.

[56] Jaemin Jung, Haeyeop Song, Youngju Kim, Hyunsuk Im, and Sewook Oh. 2017. Intrusion of software robots into journalism: The public's and journalists' perceptions of news written by algorithms and human journalists. *Computers in human behavior* 71 (2017), 291–298.

[57] Soon-Gyo Jung, Joni Salminen, Kholoud Khalil Aldous, and Bernard J Jansen. 2025. PersonaCraft: Leveraging language models for data-driven persona development. *International Journal of Human-Computer Studies* 197 (2025), 103445.

[58] Ilkka Kaate, Joni Salminen, Soon-Gyo Jung, Trang Thi Thu Xuan, Jinan Y Azem, João M Santos, and Bernard J Jansen. 2025. When Personas Talk to You: Evaluating the Evolution of User Personas from Static Profiles to Conversational User Interfaces. In *Proceedings of the 2025 ACM Designing Interactive Systems Conference*. 2350–2372.

[59] Ilkka Kaate, Joni Salminen, Soon-Gyo Jung, Trang Thi Thu Xuan, Essi Häyhänen, Jinan Y Azem, and Bernard J Jansen. 2025. "You Always Get an Answer": Analyzing Users' Interaction with AI-Generated Personas Given Unanswerable Questions and Risk of Hallucination. In *Proceedings of the 30th International Conference on Intelligent User Interfaces*. 1624–1638.

[60] Gideon Keren. 2014. Between-or within-subjects design: A methodological dilemma. In *A Handbook for Data Analysis in the Behaviorial Sciences*. Vol. 1. Psychology Press, 257–272.

[61] Nils Köbis and Luca D Mossink. 2021. Artificial intelligence versus Maya Angelou: Experimental evidence that people cannot differentiate AI-generated from human-written poetry. *Computers in human behavior* 114 (2021), 106553.

[62] Jan Kocoń, Igor Cichecki, Oliwier Kaszyca, Mateusz Kochanek, Dominika Szydło, Joanna Baran, Julita Bielaniewicz, Marcin Gruza, Arkadiusz Janz, Kamil Kanclerz, et al. 2023. ChatGPT: Jack of all trades, master of none. *Information Fusion* (2023), 101861.

[63] Michal Kosinski, Sandra C Matz, Samuel D Gosling, Vesselin Popov, and David Stillwell. 2015. Facebook as a research tool for the social sciences: Opportunities, challenges, ethical considerations, and practical guidelines. *American psychologist* 70, 6 (2015), 543.

[64] Michal Kosinski, David Stillwell, and Thore Graepel. 2013. Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the national academy of sciences* 110, 15 (2013), 5802–5805.

[65] Adam D. I. Kramer, Jamie E. Guillory, and Jeffrey T. Hancock. 2014. Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences* 111, 24 (2014), 8788–8790.

[66] V Kumar, Lerzan Aksoy, Bas Donkers, Rajkumar Venkatesan, Thorsten Wiesel, and Sebastian Tillmanns. 2010. Undervalued or overvalued customers: capturing total customer engagement value. *Journal of service research* 13, 3 (2010), 297–310.

[67] Mounia Lalmas, Heather O'Brien, and Elad Yom-Tov. 2014. Measuring User Engagement. *Synthesis Lectures on Information Concepts, Retrieval, and Services* 6 (2014), 1–132.

[68] Anders Olof Larsson. 2018. Diversifying Likes: Relating reactions to commenting and sharing on newspaper Facebook pages. *Journalism Practice* 12, 3 (2018), 326–343.

[69] Mina Lee, Percy Liang, and Qian Yang. 2022. Coauthor: Designing a human-ai collaborative writing dataset for exploring language model capabilities. In *Proceedings of the 2022 CHI conference on human factors in computing systems*. 1–19.

[70] Michael Lewis, Jeannette M Haviland-Jones, and Lisa Feldman Barrett. 2010. *Handbook of emotions*. Guilford Press.

[71] Johan Lindquist and Esther Weltevrede. 2024. Authenticity Governance and the Market for Social Media Engagements: The Shaping of Disinformation at the Peripheries of Platform Ecosystems. *Social Media+ Society* 10, 1 (2024), 20563051231224721.

[72] Fan Lu. 2024. Content Marketing Planning, Execution, and Measurement. In *Digital Content Marketing*. Routledge, 13–30. https://www.taylorfrancis.com/chapters/edit/10.4324/9781003346500-2/content-marketing-planning-execution-measurement-fan-lu


Just Accepted

[73] Jingwen Lu. 2025. Media and marketing: Research on the role of marketing suggestion in social media posting content. In *Global Dialogue on Media Dynamics, Trends and Perspectives on Public Relations and Communication*. CRC Press, 344–349.
[74] Guixun Luo, Zhiyuan Zhang, and Sumeng Diao. 2022. Empirical analysis and modelling social network user interaction behavior and time characteristics based on selection preference. *Information Sciences* 608 (2022), 1202–1220.
[75] Renkai Ma. 2023. Conceptualizing and Rethinking the Design of Cross-platform Creator Moderation. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23)*. Association for Computing Machinery, New York, NY, USA, 1–4. doi:10.1145/3544549.3577049
[76] Renkai Ma, Xinning Gui, and Yubo Kou. 2023. Multi-Platform Content Creation: The Configuration of Creator Ecology through Platform Prioritization, Content Synchronization, and Audience Management. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg Germany, 2023-04-19). ACM, 1–19. doi:10.1145/3544548.3581106
[77] N. Muhammad. 2019. An analysis to determine the most suitable type of multimedia used on Facebook social media platform. *International Journal of Advance Research, Ideas and Innovations in Technology* 5 (2019), 2146–2154.
[78] Taberez Ahmed Neyazi, Sheryl Wei Ting Ng, Mitchell Hobbs, and Audrey Yue. 2023. Understanding user interactions and perceptions of AI risk in Singapore. *Big Data & Society* 10, 2 (2023), 20539517231213823.
[79] Lene Nielsen. 2002. From user to character: an investigation into user-descriptions in scenarios. In *Proceedings of the 4th conference on Designing interactive systems: processes, practices, methods, and techniques*. 99–104.
[80] Lene Nielsen, Kira Storgaard Hansen, Jan Stage, and Jane Billestrup. 2015. A template for design personas: analysis of 47 persona descriptions from danish industries and organizations. *International Journal of Sociotechnology and Knowledge Development (IJSKD)* 7, 1 (2015), 45–61.
[81] Siti Aisyah Nurhidayah. 2025. Social Media Slang Evolution in Indonesia: A Big Data Analysis of Instagram and TikTok Hashtags (2018-2024). *Journal of Linguistics and Communication Studies* 4, 1 (2025), 9–18.
[82] Itziar Oltra, Carmen Camarero, and Rebeca San Jose Cabezudo. 2022. Inspire me, please! The effect of calls to action and visual executions on customer inspiration in Instagram communications. *International Journal of Advertising* 41, 7 (2022), 1209–1234.
[83] OpenAI. 2023. GPT-4 Technical Report. *ArXiv* abs/2303.08774 (2023). https://api.semanticscholar.org/CorpusID:257532815
[84] Gregory Park, H Andrew Schwartz, Johannes C Eichstaedt, Margaret L Kern, Michal Kosinski, David J Stillwell, Lyle H Ungar, and Martin EP Seligman. 2015. Automatic personality assessment through social media language. *Journal of personality and social psychology* 108, 6 (2015), 934.
[85] Reza Arkan Partadiredja, Carlos Entrena Serrano, and Davor Ljubenkov. 2020. AI or Human: The Socio-ethical Implications of AI-Generated Media Content. *2020 13th CMI Conference on Cybersecurity and Privacy (CMI) - Digital Transformation - Potentials and Challenges(51275)* (2020), 1–6. doi:10.1109/CMI51275.2020.9322673
[86] Meet Patel, Muskan Sanghvi, and Jignesh Vidani. 2025. Unmasking the Influencers Impact of Social Media Personalities on Gen Z Buying Decisions. *International Journal of Sustainable Applied Sciences* 3, 1 (2025), 13–30.
[87] Mark J. Pelletier, Alexandra Krallman, F. Adams, and Tyler Hancock. 2020. One size doesn't fit all: a uses and gratifications analysis of social media platforms. *Journal of Research in Interactive Marketing* (2020). doi:10.1108/jrim-10-2019-0159
[88] Giulio Perrotta. 2022. Psychopathological profiles and trends of Italian social network users (Facebook, Instagram, Twitter, and TikTok). *Annals of Psychiatry and Treatment* 6, 1 (2022), 053–061.
[89] Kay Peters, Yubo Chen, Andreas M Kaplan, Björn Ognibeni, and Koen Pauwels. 2013. Social media metrics—A framework and guidelines for managing social media. *Journal of interactive marketing* 27, 4 (2013), 281–298.
[90] Omid Rafieian and Hema Yoganarasimhan. 2023. AI and Personalization. (2023), 77–102. https://www.emerald.com/insight/content/doi/10.1108/S1548-643520230000020004/full/html Publisher: Emerald Publishing Limited.
[91] Amon Rapp, Chiara Di Lodovico, and Luigi Di Caro. 2025. How do people react to ChatGPT's unpredictable behavior? Anthropomorphism, uncanniness, and fear of AI: A qualitative study on individuals' perceptions and understandings of LLMs' nonsensical hallucinations. *International Journal of Human-Computer Studies* (2025), 103471.
[92] Jeba Rezwana and Mary Lou Maher. 2022. Understanding user perceptions, collaborative experience and user engagement in different human-AI interaction designs for co-creative systems. In *Proceedings of the 14th Conference on Creativity and Cognition*. 38–48.
[93] Richard Rogers. 2021. Visual media analysis for Instagram and other online platforms. *Big Data & Society* 8, 1 (2021), 20539517211022370.
[94] Dmitri Rozgonjuk, Cornelia Sindermann, Jon D. Elhai, and Christian Montag. 2020. Fear of Missing Out (FoMO) and social media's impact on daily-life and productivity at work: Do WhatsApp, Facebook, Instagram, and Snapchat Use Disorders mediate that association? *Addictive Behaviors* 110 (Nov. 2020), 106487. doi:10.1016/j.addbeh.2020.106487
[95] Joni Salminen, Soon-gyo Jung, Shammur Chowdhury, Sercan Sengün, and Bernard J Jansen. 2020. Personas and analytics: A comparative user study of efficiency and effectiveness for a user identification task. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–13.
[96] Joni Salminen, Soon-gyo Jung, and Bernard J Jansen. 2021. Are data-driven personas considered harmful?: Diversifying user understandings with more than algorithms. *Persona Studies* 7, 1 (2021), 48–63.

Just Accepted

[97] Francesco Salvi, Manoel Horta Ribeiro, Riccardo Gallotti, and Robert West. 2024. On the Conversational Persuasiveness of Large Language Models: A Randomized Controlled Trial. arXiv:2403.14380 [cs] doi:10.48550/arXiv.2403.14380

[98] Emanuele Sangiorgio, Niccolò Di Marco, Gabriele Etta, Matteo Cinelli, Roy Cerqueti, and Walter Quattrociocchi. 2025. Evaluating the effect of viral posts on social media engagement. *Scientific Reports* 15, 1 (2025), 639.

[99] Emily Scheinfeld and Heather L Voorhees. 2022. How Social Media, FoMO, and Isolation influence our perceptions of others who "break the rules". *Social Media+ Society* 8, 2 (2022), 20563051221103841.

[100] Bruno Schivinski, George Christodoulides, and Dariusz Dabrowski. 2016. Measuring Consumers' Engagement With Brand-Related Social-Media Content: Development and Validation of a Scale that Identifies Levels of Social-Media Engagement with Brands. *Journal of Advertising Research* 56, 1 (March 2016), 64–80. doi:10.2501/JAR-2016-004

[101] Kurt Shuster, Mojtaba Komeili, Leonard Adolphs, Stephen Roller, Arthur Szlam, and Jason Weston. 2022. Language models that seek for knowledge: modular search & generation for dialogue and prompt completion. In *Conference on Empirical Methods in Natural Language Processing*. https://api.semanticscholar.org/CorpusID:247627671

[102] Sophia Spallek, Louise Birrell, Stephanie Kershaw, Emma Krogh Devine, Louise Thornton, et al. 2023. Can we use ChatGPT for Mental Health and Substance Use Education? Examining Its Quality and Potential Harms. *JMIR Medical Education* 9, 1 (2023), e51243.

[103] Andrew T Stephen, Michael R Sciandra, and Jeffrey J Inman. 2015. The effects of content characteristics on consumer engagement with branded social media content on Facebook. *Marketing Science Institute Working Paper Series* 15, 110 (2015), 1–51.

[104] Risqo Wahid, Joel Mero, and Paavo Ritala. 2023. Written by ChatGPT, illustrated by Midjourney: generative AI for content marketing. 35, 8 (2023), 1813–1822. https://www.emerald.com/insight/content/doi/10.1108/APJML-10-2023-994/full/html Publisher: Emerald Publishing Limited.

[105] Bo Wang, Jing Ma, Hongzhan Lin, Zhiwei Yang, Ruichao Yang, Yuan Tian, and Yi Chang. 2024. Explainable fake news detection with large language model via defense among competing wisdom. In *Proceedings of the ACM Web Conference 2024*. 2452–2463.

[106] Chengliang Wang, Xiaojiao Chen, Zhebing Hu, Sheng Jin, and Xiaoqing Gu. 2025. Deconstructing University Learners' Adoption Intention Towards AIGC Technology: A Mixed-Methods Study Using ChatGPT as an Example. *Journal of Computer Assisted Learning* 41, 1 (2025), e13117.

[107] Xuena Wang, Xueting Li, Zi Yin, Yue Wu, and Jia Liu. 2023. Emotional intelligence of large language models. *Journal of Pacific Rim Psychology* 17 (2023), 18344909231213958.

[108] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. 2022. Emergent abilities of large language models. *Transactions on Machine Learning Research* (2022).

[109] Anja Wölker and Thomas E Powell. 2021. Algorithms in the newsroom? News readers' perceived credibility and selection of automated journalism. *Journalism* 22, 1 (2021), 86–103.

[110] Xin Xin, Yonghao Wang, Yiwen Zhang, Qianqian Wu, Wenmin Yang, Chenhong Yang, Rongrong Zhang, Michael T Lai, and Wei Liu. 2022. Building up personas by clustering behavior motivation from extreme users. In *International Conference on Human-Computer Interaction*. Springer, 120–131.

[111] Borchuluun Yadamsuren and Jannica Heinström. 2011. Emotional reactions to incidental exposure to online news. *Information Research* 16, 3 (2011), 16–3.

[112] Chen Yang, Xiaohong Chen, Lei Liu, and Penny Sweetser. 2021. Leveraging semantic features for recommendation: Sentence-level emotion analysis. *Information Processing & Management* 58, 3 (2021), 102543. doi:10.1016/j.ipm.2021.102543

[113] Mochen Yang, Yuqing Ren, and Gediminas Adomavicius. 2019. Understanding user-generated content and customer engagement on Facebook business pages. *Information Systems Research* 30, 3 (2019), 839–855.


## A Sample video transcript

Table 6 shows a sample video transcript related to Figure 1 discussing flood-proof bamboo housing in Pakistan.

Received 15 April 2025; revised 31 July 2025; accepted 23 July 2025

Just Accepted

Table 6. Transcript of a video discussing flood-proof bamboo housing in Pakistan

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| Could these bamboo houses be a solution to Pakistan's climate crisis?<br>Pakistan's first woman architect is working in rural areas to make flood-proof houses.<br>The world today actually needs something like this, which will be zero carbon. And my motto—I don't know whether you know—is zero carbon, zero waste, zero donor, which I think leads to zero poverty. So this is what I'm trying to do. And I hope that I manage to get to as many people as possible.<br>82-year-old Yasmeen Lari wants Pakistan to have 1 million homes made from affordable materials.<br>In some of the areas worst hit by Pakistan's deadly 2022 floods.<br>At least 1,739 people were killed and millions have been displaced.<br>Scientists have linked the floods to intense, "record-breaking monsoonal rainfall."<br>One-third of Pakistan was underwater after the 2022 floods.<br>My dream for some years now is that we should build in a manner—or that I should get the skills of building into the hands of everybody in my country, and the poor particularly, who can build so that they will not be displaced. So this has been something that I've been wanting to do.<br>And now I find that with this disaster, I'm getting a chance to be able to spread that message.<br>Pakistan has the fifth-largest population in the world.<br>But it is responsible for less than 1% of global greenhouse gas emissions.<br>Pakistan's most vulnerable people live in areas that are at risk because of poor infrastructure.<br>The elevated houses that Lari has designed can withstand rushing water.<br>Everything is elevated so that the waters coming, they won't affect anything. And then bamboo is something that I've been using since 2009, so I learned how to use it and we've been using it in earthquake areas as well as flood areas. And they have survived very well because they are very well designed. |

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