IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 10 September 2025, accepted 7 October 2025, date of publication 15 October 2025, date of current version 22 October 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3621667

RESEARCH ARTICLE

Information Characteristics and Social Media Information Sharing: Insights From Elaboration Likelihood Model (ELM) for Misinformation Mitigation

JUANITA ZAINUDIN[1,2], NAZLENA MOHAMAD ALI[1], ALAN F. SMEATON[3], (Fellow, IEEE), AND MOHAMAD TAHA IJAB[1]

[1]Institute of Visual Informatics (IVI), Universiti Kebangsaan Malaysia, Bangi 43600, Malaysia
[2]Faculty of Computing and Multimedia, Universiti Poly-Tech Malaysia, Kuala Lumpur 56100, Malaysia
[3]Insight Centre for Data Analytics, Dublin City University, Dublin 9, D09 V209 Ireland

Corresponding author: Nazlena Mohamad Ali (nazlena.ali@ukm.edu.my)

This work was supported in part by the Universiti Kebangsaan Malaysia Research Grant GUP-2023-036.

ABSTRACT The rapid dissemination of information on social media has many positives but has also raised significant concerns regarding misinformation, making it crucial to understand the factors driving information-sharing behavior. This study employs the Elaboration Likelihood Model (ELM) with its dual processing pathways (central and peripheral route processing) to identify key information characteristics influencing information-sharing behavior on social media. Through Reflexive Thematic Analysis (RTA) of 92 viral tweets from three Malaysian news channels between January and October 2024, five key themes emerged: Social Interest, Political Interest, Visual Appeal, Credible Sources, and Emotional Appeal. Illustrative case studies of viral Malaysian tweets were analyzed, revealing how different information characteristics trigger varying cognitive processing routes. Our findings indicate that Social Interest and Political Interest align with central route processing, require deeper cognitive engagement. Conversely, Visual Appeal, Credible Sources, and Emotional Appeal follow the peripheral route processing, relying on heuristic cues. Importantly, many viral tweets engage mixed processing, highlighting the need for hybrid interventions. Building on these insights, the study offers practical guidance for stakeholders: policymakers can enforce regulations and promote awareness, platforms can add credibility markers and prioritize trusted sources, educators can teach media literacy, and users can adopt a ‘‘pause-and-verify’’ approach. Collectively, these efforts can help create a digital ecosystem that balances user engagement with accuracy in online information sharing.

INDEX TERMS Information characteristics, information sharing, misinformation, intervention strategy, social media, elaboration likelihood model.

I. INTRODUCTION

The rise of digital media has shifted the traditional news and information consumption model, where information was primarily consumed through verified sources such as newspapers and television, to a decentralized system where anyone can produce and share content. This shift has created an environment where misinformation spreads rapidly, often leveraging the same engagement-driven mechanisms as legitimate information but ultimately driven by the social media platforms' advertising policies. Information characteristics have a significant influence on users' dissemination behavior on social media [1]. Social media posts that went viral are typically influenced by various factors, including the content's topic, emotional appeal, visual appeal, and source credibility. In this study, the term viral refers to tweets

The associate editor coordinating the review of this manuscript and approving it for publication was Olarik Surinta.

with a threshold of at least 1000 retweets. Considering the rapid spread of information on social media, it is essential to comprehend how users interact with and interpret various types of information to create effective interventions against misinformation. Previous research indicates that people usually share content due to its vividness, relevance, credibility, emotional impact, and visual appeal [1], [2], [3]. Misinformation often uses these traits to seem legitimate, using sensational and emotionally charged material to bypass critical scrutiny [4], [5]. Thus, the Elaboration Likelihood Model (ELM) is a robust framework for examining these interactions by distinguishing between central and peripheral information processing routes. While some users thoughtfully assess the information (central route), others depend on heuristic signals like visual and emotional appeal (peripheral route). Since misinformation can propagate through both cognitive pathways, recognizing essential characteristics that affect information-sharing behaviors can aid in developing intervention strategies to limit its spread. Therefore, this study aims to address the following research question:

RQ: What are the characteristics of information that influence information-sharing behavior on social media?

We utilize ELM theory to analyze viral tweets from Malaysian social media news channels. It identifies the key characteristics of information that drive behavior related to information sharing on the X (formerly Twitter) platform. By understanding these attributes, the study can guide intervention strategies aimed at promoting responsible information-sharing practices. Additionally, by examining how cognitive engagement varies across different content types, the study provides insights into how misinformation can be countered through tailored interventions that encourage critical evaluation and responsible sharing behavior.

This paper is organized into six sections. Following this introduction, Section II reviews the relevant literature, establishing the theoretical context. Section III outlines the research methodology employed in the study. Section IV presents the research results, while Section V discusses the implications of these findings. Finally, Section VI concludes the paper, summarizing key insights, limitations, and suggesting directions for future research.

II. LITERATURE REVIEW

A. INFORMATION-SHARING BEHAVIOR ON SOCIAL MEDIA IN MALAYSIA

Information in social media posts often drives high levels of user engagement and discussion, particularly when it is susceptible to virality, especially if the content relates to social issues, political matters, or emotional appeal. Hence, it provides a valuable case for examining the characteristics influencing sharing behavior [6]. Furthermore, content shared on social media is often a target for misinformation campaigns, which can have significant societal implications [7].

In Malaysia, a survey conducted by the Malaysia Communications and Multimedia Commission (MCMC) [8] revealed that 94.1% of Internet users use social networking platforms. These serve as critical channels for information dissemination and engagement, with platforms like Facebook, Instagram, TikTok, and X playing significant roles in how users interact with and share content. Facebook continues to be Malaysia's leading platform for information consumption, with a broad user base and lively discussions [8]. In contrast, Instagram and TikTok focus on telling stories visually, which makes them powerful platforms for sharing information through short videos and infographics [9]. However, X was selected for this study due to its real-time information dissemination and high user engagement with post content.

X, formerly known as Twitter, is essential for understanding how we share information on social media. Recent data from Bernama show that about 30% of Malaysians use X daily, underscoring this platform's significance for our research [10]. X is unique among other social media platforms because it focuses on quick interactions such as retweets, replies, and quote tweets, which spark immediate discussions and enhance the visibility of shared content [11], [12]. Given these characteristics, X is an ideal environment for exploring how information spreads and analyzing sharing behaviors, particularly in Malaysia. Additionally, the platform's open nature and popularity for discussing political, social, and cultural issues in Malaysia further enhance its suitability for this research, as it captures diverse audience interactions and behaviors.

On the X platform, a tweet goes viral quickly when it gets a lot of engagement, like retweets and likes. It usually gets more attention than the number of followers the channel has. This phenomenon is influenced by various factors, including the content of the tweet, its timing, and the social network dynamics surrounding it. The definition of a viral tweet has been approached in several ways across the literature. Elmas et al. [13] define viral tweets as those that have been retweeted at least T times, with T set at thresholds of 50, 100, 500, or 1000. Their measurement of virality primarily relies on the number of retweets as a proxy. In a similar study, Kennedy et al. [14] examined misinformation and also utilized the number of retweets as a key indicator of virality, defining a viral tweet as an original tweet (not a retweet or quote tweet) that achieves at least 1000 retweets, thus indicating substantial reach and influence within misinformation narratives. Additionally, Han D [15] emphasized the importance of retweets as a critical measure of virality, highlighting that retweets facilitate the spread of information and its cascading effects, whereas favorites only signify popularity. Expanding on these ideas, Maldonado-Sifuentes et al. [16] introduced an influence score, incorporating follower count, favorites, and retweets, and employed 'RoBERTa' to predict tweet virality based on a corpus of 5,000 annotated tweets. In contrast, Garimella & West [17] defined a tweet as viral if it received more retweets than 90% of the user's previous posts. While specific threshold values for defining virality vary across platforms and content types, these studies primarily use engagement metrics to assess the virality of tweets.

The dynamics of social media platforms and the nature of shared information significantly influence how widely information is disseminated. The way information is structured, perceived, and interpreted plays a crucial role in determining its reach and impact. Therefore, it is essential to examine the key characteristics of information to gain a better understanding of sharing behavior. This understanding is a critical first step before exploring interventions for misinformation. This process involves reviewing definitions and identifying the key characteristics of information on social media, drawing from previous studies. The following subsection will delve into the concept of information.

B. INFORMATION CONCEPTS

Information may be interpreted differently depending on its nature and disciplines. Information is processed raw data that holds meaning and can be conveyed in various ways to help people understand, such as through text, graphs, images, and even videos. In quantum physics and thermodynamics, information is linked to entropy, energy states, and the fundamental structure of reality [18]. In philosophy, information is often examined in epistemology, focusing on knowledge formation and truth [19]. In psychology, people experience information through their senses, thoughts, and feelings [20].

Information in the context of social media refers to the content that is shared, created, and consumed by users on social media platforms. It includes various types of modalities such as text, images, animation, and videos [21]. The information shared on social media can be personal, shopping-related information, health-related information, and knowledge that leads to a variety of outcomes [22]. It serves as a way for users to make sense of situations, gather consensus from friends, and seek both informational and socio-emotional support. This diverse range of information not only shapes user interactions and engagement but also influences decision-making processes, opinions, and behavioral outcomes in the digital ecosystem.

The vast amount of information generated on social media platforms presents significant challenges for users and researchers. However, it also enables the study of social phenomena and a better understanding of user behavior. A considerable study area involves information disorders on social media, encompassing inaccuracies, misleading content, and misinformation. Unfortunately, many current countermeasures have been unsuccessful in addressing these disorders. They focus too heavily on fact-checking user posts while overlooking the contextual and psychological factors involved in the spread of misinformation [23], [24]. Therefore, it is crucial to explore and identify the key characteristics of information that can influence social media users for dissemination. For instance, Yang et al. [1] stated that various factors affect how information spreads on social media. These include the roles of users, the content of the messages, the interactions between that content and individuals, and the overall context. Notably, the type of article and its relevance to the title are also key factors in this process.

Information characteristics in social media refer to the inherent attributes of content that influence how individuals perceive, comprehend, and disseminate information. These traits are vital in determining how information circulates, influencing whether it captures attention or diminishes within online discussions. Prior studies on information-sharing behaviors in social media have explored the characteristics of information that drive engagement and influence users' likelihood of sharing content. Through a conceptual analysis of previous research, scholars have identified several key factors that most significantly drive engagement and influence information-sharing behavior, including information quality, source credibility, visual appeal, emotional appeal, sensationalism, and social impact. These factors significantly affect the chances of users engaging with and sharing content. Table 1 presents the findings of prior studies on key information characteristics that influence information-sharing behavior on social media. It synthesizes these findings, detailing the description and impact of each characteristic on sharing behavior.

Various theoretical perspectives can explain how these characteristics affect information processing, shaping how individuals interact with and evaluate information, including the Elaboration Likelihood Model (ELM), Heuristic-Systematic Model (HSM), Uses and Gratifications Theory (UGT), Cognitive Dissonance Theory (CDT), Dual-Process Theory, and Theory of Planned Behavior (TPB). Each theory provides essential insights into various aspects of information consumption and persuasion. This study adopts the ELM as its primary framework due to its emphasis on cognitive engagement, dual-processing model, and close alignment with the dynamics of social media and contexts involving misinformation. This makes it particularly effective for analyzing and shaping information-sharing behaviors. Additionally, ELM has proven to be a practical framework for explaining how information can affect individual attitudes and behaviors [25]. To provide more justification, subsection II-D elaborates on the reasons for using ELM.

C. ELABORATION LIKELIHOOD MODEL (ELM)

The Elaboration Likelihood Model (ELM) is a dual-process theory of persuasion that describes how people process persuasive messages and develop attitudes. It proposes that individuals can process these messages through two distinct routes: the central route and the peripheral route [49], [50]. It serves as the foundation for understanding how information characteristics influence information-sharing behavior on social media. ELM theory explains that when individuals perceive information as highly relevant or personally significant, they engage in deeper cognitive processing through the central route [51]. During this process, they assess the quality of the arguments, the complexity of the message,

TABLE 1. Conceptual analysis of key information characteristics influencing information-sharing behavior on social media.

Information Characteristics	Description	Impact on Sharing Behavior	References
Information Quality	Content that is systematically structured with a clear objective, adequate depth, relevant information, and strong arguments.	• High-quality information enhances credibility and trust, making it more likely for users to share it.	[1], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35]
Source Credibility	Content from a trustworthy and reliable authority.	• Credible sources increase engagement and reshares due to trust in the source.	[26], [30], [36]
Visual Appeal	Content that includes elements such as images, infographics or videos.	• Visually appealing significantly affects engagement and information dissemination.	[1], [34], [37], [38]
Emotional Appeal	Content that includes emotional elements, such as fear, anger, joy, or sadness.	• Emotionally charged content spreads rapidly, particularly negative or shocking information. • Messages that evoke strong emotions (such as fear, anger, joy, or sadness) have been found to trigger higher engagement levels.	[27], [28], [29], [36], [39], [40], [41], [42], [43]
Sensationalism	Content that uses exaggeration, sensationalist framing, clickbait headlines, or shocking elements to attract attention and drive virality	• Sensationalized content exploits users' curiosity and is common in viral journalism. • However, this type of information can lead to the sharing of misinformation.	[30], [44], [45], [46], [47]
Social Impact	Content with social influence and significance includes shares from personal connections, visible popularity or endorsements, and alignment based on group identity.	• Users are more likely influenced by how other interact with content, which increases the potential for virality. • content that is relevant to the public and addresses socially important issues is more likely to achieve virality.	[29], [40], [42], [48]

and its credibility before arriving at a conclusion. It entails careful reasoning, evaluating evidence, and logically determining the message's validity. On the other hand, when motivation or cognitive ability is low, people tend to rely on the peripheral route [52]. In this case, heuristic cues and emotional factors, such as visual appeal and source appeal, influence their judgment with minimal scrutiny. Here, users might have an instinctive emotional reaction, forming swift impressions based on superficial traits rather than conducting a rational assessment. These cognitive and emotional reactions ultimately shape whether users choose to share information, often reinforcing their preexisting attitudes and beliefs.

Elaboration operates along a spectrum, determining the extent to which individuals process information (see Fig. 1). While the ELM defines 2 broad modes of processing, the central route (high elaboration) and the peripheral route (low elaboration), it is important to recognize that elaboration exists on a continuum rather than as a strict dichotomy [49]. At the low elaboration end of the spectrum, individuals engage in minimal cognitive effort, relying almost entirely on heuristic cues such as emotional appeal, source credibility, and visual aesthetics to make judgments [53]. At the high elaboration end, individuals engage in extensive cognitive effort, carefully evaluating message arguments, analyzing factual accuracy, and considering logical reasoning before forming an opinion [54].

Motivation and ability are key determinants of elaboration and influence the likelihood of persuasion. Motivation is driven by personal relevance and interest. Higher motivation leads to deeper processing via the central route, while lower motivation results in reliance on superficial cues through the peripheral route [49], [51]. Ability refers to cognitive capacity; individuals with prior knowledge, time, and mental resources engage in critical thinking, whereas distractions or complexity lead to heuristic-based processing [49], [52]. When both motivation and ability are high, persuasion is more durable (central Route); if either is low, attitude change is temporary (peripheral Route).

While ELM provides a valuable framework, it has been criticized for treating persuasion as a strict dichotomy between central and peripheral processes [55], [56]. This critique is especially salient for social media, where multimodal messages (text, images, videos, hashtags, and endorsements) encourage mixed or hybrid activation of routes rather than dichotomous processing. In practice, message elaboration frequently involves hybrid or mixed processing [57], [58]. Individuals may simultaneously assess the quality of arguments while being influenced by heuristic cues. Recent studies within the ELM suggest that users in multimodal environments, such as social media, typically begin with quick judgments but shift to more critical evaluations when they encounter conflicting cues or when the information becomes more relevant [59]. Additionally, recent advancements in ELM suggest that digital persuasion is influenced by contextual factors such as platform strategy, political polarization, and issue involvement [60], [61]. This challenges the traditional linear assumptions of the model. Guided by these critiques, the present study treats central-peripheral distinctions as analytical categories or sensitizing concepts,

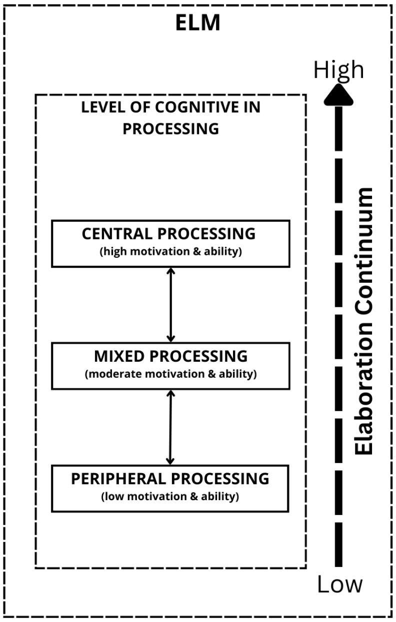


FIGURE 1. Elaboration likelihood continuum in ELM [49], [59].

explicitly allowing for central, peripheral, or mixed processing in the analysis.

ELM's adaptability has made it a valuable framework in other digital communication contexts besides ours. Studies have applied it to brand promotion on social media [62], persuasive advertising in consumer decision-making [63], and enterprise support for creative information publishers [64]. It has also been utilized in digital persuasion for vaccinations [65], examining online health information adoption [66], health communication through infographics [67], and persuasion in e-learning through gamification [68]. Additionally, [25] highlights its role in shaping consumer attitudes and behaviors, reinforcing its importance in digital marketing. Beyond marketing, ELM has also been applied to analyze user engagement behaviors (e.g., forwarding, commenting, and liking) in microblogs [69]. These diverse applications underscore ELM's appropriateness in understanding digital interactions, particularly how individuals process and share information in online environments, which is why this framework was selected as the theoretical foundation for this study, as shown later in this paper.

The ELM model is a dynamic framework because it adopts a flexible approach to incorporating new and diverse variables [49]. Unlike other theories, ELM does not mandate specific variables, allowing researchers to focus on a subset of constructs or introduce new ones to suit different contexts [58]. This study builds on this adaptability by identifying the characteristics of viral tweets that influence information-sharing behavior on social media. By leveraging ELM, this study aims to establish a structured framework for understanding how information characteristics influence persuasion and drive information dissemination. The constructs

TABLE 2. Constructs from prior ELM research in digital contexts.

Processing Mode	Description	Example Constructs Commonly Used	References
Central (high elaboration)	This route involves high cognitive processing when individuals are motivated and capable of evaluating information deeply.	• Argument quality • Content quality • Content richness • Content relevance • Content type	[27], [51], [69], [70], [71], [72], [73], [74], [75], [76], [77], [30], [78], [79], [80]
Peripheral (low elaboration)	This route involves low cognitive processing, relying on surface-level cues like visuals, emotions, and source appeal.	• Credible sources • Visual appeal • Emotional appeal • Social influence	[27], [51], [62], [69], [70], [73], [77], [78], [79], [80], [81], [82], [83], [84], [85]
Mixed (hybrid elaboration)	Reflects contemporary critiques of ELM: users often process central arguments and peripheral cues simultaneously, especially in multimodal and interactive social media environments.	• Contextual factors (platform strategy, political polarization, issue involvement)	[55], [56], [60], [61]

derived from ELM serve as guidelines for determining the most relevant information characteristics in the context of social media virality. Table 2 summarizes the ELM constructs utilized by previous researchers in digital contexts.

D. RELEVANCE OF ELM TO THE STUDY

ELM stands out among various information processing theories as the most suitable framework for studying information-sharing behavior on social media, particularly in combating misinformation. The indicator of ELM to be chosen is because of these five key indicators: 1) information processing theory perspective, 2) incorporation of psychological factors (particularly cognitive involvement), 3) alignment with social media context, 4) empirical support, and 5) relevance to designing intervention strategies.

ELM aligns with information processing theory, making it suitable for the study's objective. Additionally, ELM explicitly incorporates psychological factors, particularly in cognitive processing, addressing the crucial gap identified in recent research on misinformation intervention strategies, which often overlook psychological factors [86]. According to Petty and Cacioppo [49], Petty and Brinol [50], ELM emphasizes cognitive involvement as a crucial factor in how messages influence attitudes, which is why it was selected to meet the second indicator.

Moreover, this theory fits well within social media environments. It is versatile, considering all types of information by acknowledging that individuals process messages differently depending on their moods, abilities, and motivations [58]. Numerous prior studies on social media have utilized ELM theory, validating its relevance for application [27], [28], [32], [65]. Importantly, ELM has also provided a foundation for designing intervention strategies that promote critical content evaluation and reduce the spread of misinformation by leveraging the central route of processing. These strengths make ELM a robust and well-rounded theory for addressing the study objectives.

To further establish ELM's suitability for this research, a systematic comparison was conducted with other relevant theoretical frameworks. This comparative analysis relied on the same indicators previously mentioned. When compared to the Heuristic-Systematic Model (HSM), which also features dual modes of information processing, ELM offers a broader focus on persuasion and attitude formation, making it more applicable to this study. HSM's emphasis on heuristics and systematic processing is practical but lacks the nuanced exploration of motivation, ability, and message characteristics that ELM provides [87]. Similarly, while Uses and Gratifications Theory (UGT) effectively identifies user motivations for sharing content, it does not explain the cognitive processes behind how people evaluate and process information [88]. Cognitive Dissonance Theory (CDT) explains how people experience psychological discomfort when their beliefs or behaviors conflict and how this motivates them to reduce that discomfort [89]. However, it primarily emphasizes resolving inconsistency rather than outlining specific cognitive processing pathways or the mechanisms behind message interpretation and persuasion. Whereas Dual-Process Theory shares conceptual similarities with ELM, outlines two types of information processing: automatic (System 1) and analytical (System 2). Nonetheless, it is mostly descriptive and helpful for understanding decision-making, but less prescriptive because it lacks clear guidance for designing interventions [90]. Lastly, the Theory of Planned Behavior (TPB) explores the roles of attitudes, subjective norms, and perceived behavioral control in shaping intentions, thereby providing valuable insights into the motivation behind sharing behaviors. However, TPB does not delve into the cognitive processes involved in evaluating information [91], which are central to this study.

In conclusion, while several theories contribute valuable perspectives, ELM stands out for its comprehensive focus on cognitive involvement, strong empirical foundation, alignment with social media dynamics, and practical relevance for designing intervention strategies to combat misinformation. Recent refinements of ELM also emphasize hybrid or mixed processing routes in digital persuasion, which enhance its adaptability to the complex and multimodal nature of social media contexts [59]. In these environments, mixed processing can occur, reflecting the intricate ways in which digital audiences engage with content. This study approaches the central-peripheral distinction as a set of sensitizing concepts rather than rigid categories, which allows for a more nuanced analysis. By adopting a continuum-based perspective, the study harnesses the model's flexibility and addresses critiques regarding linearity. This approach strengthens ELM's applicability compared to alternative frameworks, providing a deeper understanding of the multi-layered processes through which digital audiences evaluate and share content in fast-paced environments like social media. Table 3 summarizes the comparison among these theories.

III. METHODOLOGY

This study is situated within a constructionist-interpretivist research paradigm, which posits that knowledge is socially and contextually constructed rather than objectively discovered. This perspective emphasizes that meaning is shaped by subjective, reflexive, and situational factors, with understanding emerging through ongoing interaction between the researcher and the data. In this view, knowledge is something we actively build together, influenced by the researcher's positionality and the contextual details within the dataset.

This study employs a qualitative approach to analyze the dataset and identify the characteristics of information that influence sharing behavior on the X platform, using Reflexive Thematic Analysis (RTA), as conceptualized and refined by Braun and Clarke [92], [93]. RTA was chosen for its epistemological flexibility and interpretative depth, facilitating the identification of latent meaning structures within users' engagement with information, in contrast to positivist approaches such as codebook thematic analysis or coding reliability methods, which operate within predetermined analytical frameworks [93]. The reflexive component of RTA enables a critical examination of how the researcher's positionality influences the analytical process, thereby enhancing methodological transparency [94]. As RTA recognizes the active role of the researcher, reflexivity was maintained throughout the process by acknowledging the researcher's background, assumptions, and analytical lens when engaging with the data.

This study primarily followed an inductive approach in the RTA process, with initial coding guided by patterns of meaning that naturally emerged from the data. RTA supports an iterative, organic analysis where the researcher plays an active role in constructing themes through reflexive and thoughtful engagement with the dataset [95], [96]. However, a deductive component was also included to ensure that the themes aligned with the research questions and that data-driven insights remained relevant to the study's objectives. The thematic development was informed by the ELM, which explains how individuals process and evaluate information via two routes: the central (high cognitive) and peripheral (low cognitive) pathways. This framework offered valuable interpretive support for understanding the complex ways users engage with digital content. While theme construction followed reflexive engagement with the data, the final theme labels were intentionally aligned with ELM

TABLE 3. Comparative framework for theory selection and justification.

Theory	Information processing theory	Incorporating psychological factors (cognitive involvement)	Alignment with social media context	Empirical support	Relevance to design intervention strategy
Elaboration Likelihood Model (ELM)	Yes (dual-processing framework)	Strong (explicitly focuses on motivation and ability influencing cognitive involvement)	High (accounts for central and peripheral cues such as source credibility and emotional appeal on social media)	Strong (widely applied in marketing, social media, and communication research)	High (provides actionable strategies by promoting critical evaluation via the central route)
Heuristic-Systematic Model (HSM)	Yes (heuristic and systematic processing)	Moderate (focuses on cognitive shortcuts but less detailed in addressing ability and motivation than ELM)	Moderate (relevant for explaining heuristic shortcuts online, but less developed for hybrid/multimodal contexts)	Moderate (used in studies on decision-making and message evaluation)	Moderate (useful for understanding heuristics but less practical for developing interventions)
Uses and Gratifications Theory (UGT)	Partially (focuses on user motivations, not message processing)	Weak (psychological effects mostly via satisfaction and attitude, not cognitive involvement)	High (widely applied to understand social media engagement and motivations)	Moderate (supported in communication and social media research)	Moderate (helps understand motivations for sharing, but limited guidance for interventions targeting critical evaluation or misinformation prevention)
Cognitive Dissonance Theory (CDT)	Indirectly (focuses on resolving conflicting cognitions rather than processing external messages)	Weak (focuses on discomfort from inconsistency rather than active cognitive engagement)	Low (not specifically tailored for social media dynamics)	Strong (widely supported through classic and modern experiments on attitude and behavior change)	Low (explains why people may change beliefs after acting, but limited guidance for preventing misinformation or promoting proactive evaluation)
Dual-Process Theory	Yes (System 1: automatic, System 2: analytical)	Moderate (addresses cognitive involvement conceptually but lacks a focus on persuasion or motivation)	Moderate (general framework, helps explain intuitive vs. reflective reactions online, but less specific to social media cues)	Moderate (strong in psychology and decision-making research, but less applied in communication or misinformation studies)	Low (conceptually rich for explaining processing differences but lacks direct mechanisms for guiding interventions in misinformation contexts)
Theory of Planned Behavior (TPB)	Partially (focuses on attitudes, norms, and perceived behavioral control; does not model detailed message processing)	Moderate (psychological factors included but lacks detailed cognitive processing of messages)	Moderate (explains intention-driven behaviors like sharing on social media but not the cognitive evaluation of content)	Strong (widely applied in behavioral and social research)	Moderate (useful for designing interventions targeting behavioral intentions, but limited guidance for strategies focus on message evaluation)

categories to facilitate integration with the conceptual model tested in later stages of the study. These short-form labels represent condensed, theory-informed encapsulations of the meaning patterns interpreted during analysis. Incorporating ELM strengthened the analytical power and validity of the RTA [94]. This hybrid approach, blending inductive data exploration with theoretically grounded interpretation, represents a methodological advance beyond traditional thematic analysis, as described by Fereday and Muir-Cochrane [97]. As Braun and Clarke [93], [95] note, coding and analysis often involve a mix of inductive and deductive strategies, rather than fitting neatly into one approach.

To enhance the credibility of our findings, we employed several rigorous strategies, including maintaining transparency throughout the analytical process, providing rich and detailed descriptions of the identified themes, engaging in ongoing reflexive journaling to reflect on our biases and perspectives, and ensuring a clear alignment between the data and interpretation. Additionally, all data sourced from public tweets were anonymized where appropriate, and we adhered to ethical standards for digital research.

A. DATA COLLECTION

Data were extracted using Instant Data Scraper, a web scraping tool designed to collect publicly accessible data from the X platform. The tool facilitated the systematic retrieval of viral tweets from three prominent Malaysian news channels: Astro Awani, Bernama TV, and Free Malaysia Today. The data collection spanned 10 months from January-October 2024, focusing on highly visible posts to ensure analytical significance. The prioritization of viral tweets is grounded in their representation of content with substantial audience reach and influence, thereby providing a more meaningful insight into the dynamics of persuasion and sharing behaviors compared to random or low-engagement posts.

The extraction process yielded a total of 92 viral tweets, comprising 60 from Astro Awani, 6 from Bernama TV, and 26 from Free Malaysia Today. The selection of these three Malaysian news channels was intentional, aiming to capture a diversity of perspectives. Astro Awani represents corporate-driven journalism, Bernama TV reflects government narratives, and Free Malaysia Today offers independent perspectives. This diversity is instrumental in capturing varying audience preferences, content framing styles, and sharing behaviors. Moreover, these channels address issues specific to Malaysia, ensuring that the analysis remains localized and contextually relevant, thereby enhancing the robustness of the analysis.

Furthermore, news articles are among the most frequently shared content on social media platforms in Malaysia [8]. They often drive high engagement and discussion, especially on social, political, and inspirational topics, making them highly shareable and a valuable case for studying what drives sharing behavior [6], [98]. Additionally, news content is a common target for misinformation campaigns, which can carry significant societal implications [7]. By focusing on Malaysian news outlets such as Astro Awani, Bernama TV, and Free Malaysia Today, this study can identify key information characteristics that influence sharing behavior, providing insights into how misinformation spreads and informing strategies to mitigate its impact.

While the dataset is relatively modest in size, it is essential to acknowledge that qualitative thematic research, as emphasized by Braun and Clarke [92], Guest et al. [99], and Wutich et al. [100] prioritizes the richness of information and contextual depth over sheer sample size. In fact, Wutich et al. [100] noted that 20-30 documents are often sufficient in reflexive thematic analysis, which further underscores that the present dataset of 92 viral tweets exceeds this threshold and is therefore suitable for generating meaningful insights. This focus aligns with the study's objective of identifying information characteristics that influence sharing behavior, which can be used in constructing an intervention model rather than achieving statistical representativeness across the entire spectrum of social media usage.

In this study, a tweet is considered viral based on the number of retweets it receives [13], [15], with a threshold of at least 1000 retweets used to define viral tweets. This threshold is supported by prior researchers who consistently selected this value as a significant marker [13], [14]. Following extraction, the dataset underwent comprehensive cleaning and preparation to ensure analytical rigor.

B. DATA TRANSCRIPTION

The data transcription process followed a verbatim approach to preserve the original structure and wording. This approach allowed us to keep the true voice of each user intact during the transcription process. The data were cleaned by removing all unnecessary characters and symbols before undergoing the transcription process. The transcribed tweets were then organized in a tabular format, with each documented by a unique Tweet ID (refer to our dataset [101]). To ensure reliability, tweets were cross-verified for consistency in meaning, and IDs were stored for traceability during analysis. This process enabled an accurate representation of information-sharing behavior for subsequent thematic analysis.

C. DATA ANALYSIS

This study followed the six-phase RTA process as outlined by Braun and Clarke [92], [95], which emphasizes the iterative, flexible, and reflective nature of qualitative analysis. The practical application of these phases was guided by the interpretive approach demonstrated by Byrne [102], which supports active researcher engagement and ongoing reflexivity throughout the analytic process.

In line with RTA principles, we engaged in deep familiarization with the data, reading and re-reading the dataset while documenting early impressions and analytic insights. Rather than applying a rigid, linear structure, the phases of RTA were approached recursively, with movement back and forth between phases to refine codes, patterns of meaning, and emerging themes. This process required sustained and thoughtful interaction with the data, allowing themes to evolve organically while being shaped by the researcher's interpretive lens.

Reflexivity was maintained throughout each phase, acknowledging the researcher's subjectivity and role in meaning as central to the analytic process. Since RTA is rooted in a constructionist-interpretivist framework, it does not pursue data saturation in the conventional way. Instead, the focus was on thematic adequacy, where themes are considered sufficiently developed to address the research questions effectively. This methodology aligns with Braun and Clarke's perspective that meaning is actively constructed, not passively uncovered, through the researcher's ongoing reflexive engagement data [94].

As previously mentioned, a deductive approach was adopted, utilizing ELM theory as a framework for sensitizing concepts. During the coding and theme review stages (phases 4-6) of RTA (refer to Fig. 2), particular attention was given to indicators of ELM constructs, namely central and peripheral processing. This integration between ELM and RTA structured the analytic process, connecting theoretical information-processing routes with emerging data-driven themes. Initial codes were generated inductively from the data itself, while ELM constructs guided the grouping, interpretation, and naming of themes. This ensured that the analysis moved beyond surface-level categorization to capture underlying elaboration processes. Theory-informed reflexivity also supported the determination of whether themes predominantly represented central or peripheral processing, without imposing a rigid, predetermined codebook.

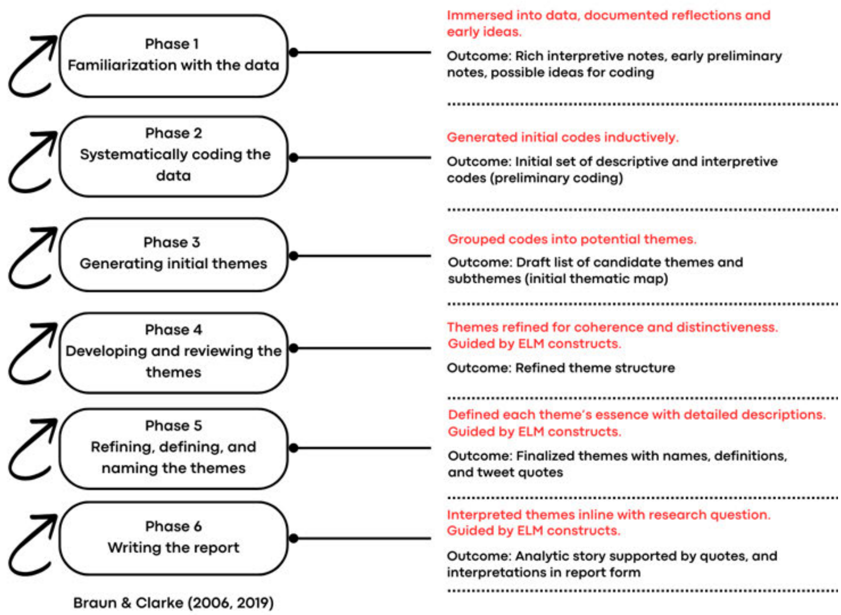


FIGURE 2. RTA six-phase approach.

Fig. 2 illustrates the RTA six-phase process, which includes: 1) familiarizing with the data, 2) systematically coding the data, 3) generating initial themes, 4) developing and reviewing the themes, 5) refining, defining, and naming the themes, and 6) writing the report.

1) PHASE 1: FAMILIARIZATION WITH THE DATA

The analysis process began with data familiarization. Viral tweets were extracted using Instant Data Scraper, cleaned in Excel, and converted to PDF format for analysis in NVivo (version 15). We engaged with the dataset by reading each tweet multiple times, undergoing several iteration cycles.

In the first cycle, notes were not yet taken; instead, the dataset was actively observed and immersed in. The second cycle involved casual observations of initial trends, during which we documented our thoughts and feelings about the data and analytic process in preliminary notes. The subsequent round consisted of re-reading each dataset multiple times, conducting initial observations, and systematically and manually writing interpretive notes for each tweet.

In summary, the preliminary notes outline the main patterns in the dataset, while the interpretive notes concentrate on individual tweets. Both sets of notes were helpful and guided the subsequent coding process. Fig. 3 shows an example of preliminary notes recorded during the familiarization and engagement phase.

Preliminary Notes (Phase 1)
Duration: 1-8 November 2024 (1 week)

Reflexive Comments (All dataset)
1. Multimodal Features Influence Perception
"During my observation, I noticed that tweets present multiple features—such as text, visuals (images or videos), hashtags, external links, and engagement metrics—that collectively shape how the content is perceived and interacted with."

2. Visual Content Enhances Message Clarity and Credibility
"I've noticed that I pay more attention to visual content on social media because images and videos enhance the message. They not only make the content easier to understand but also increase its trustworthiness. As the saying goes, *a picture is worth a thousand words*."

3. Emotional Sensitivity to Family Loss and National Framing
"I find myself emotionally moved by the stories involving family loss and sacrifice. I also noticed a recurring tone of national unity and moral outrage. This might shape how I view posts with religious or political framing. I must be cautious not to let my assumptions about political motivation over code emotional cues."

FIGURE 3. Example of preliminary notes taken in Phase 1.

2) PHASE 2: SYSTEMATICALLY CODING THE DATA

Initial codes were developed inductively, carefully grounded in both the semantic (explicit) and latent (underlying) content of the data. The coding process involves creating concise, descriptive labels (shorthand) that capture relevant aspects of the information related to the research question. To ensure thoroughness, the entire dataset was systematically reviewed, giving equal attention to each piece of data and highlighting interesting or potentially informative elements that may contribute to developing overarching themes.

Initially, coding was performed manually without relying on any predefined framework. This inductive methodology facilitated the development of 45 distinct codes, encompassing content highlights, sourcing, persuasive cues, and engagement patterns. NVivo software was employed to support efficient data organization and retrieval throughout the analytical process. Codes are meant to be brief yet detailed enough to stand alone, revealing commonalities among data items with

TABLE 4. Sample of the code tracking during preliminary coding.

Tweet ID	Tweet Post	Iterative 1	Iterative 2	Iterative 3	Iterative 4
Awani 3	Eid tomorrow!!! Hari Raya Aidilfitri for all states is declared throughout Malaysia on Wednesday 10 April 2024	• High cultural salience • Official announcement of national religious holiday • Emotionally uplifting event • Supporting videos • Provide hashtags • Source by trusted private media company	• Timeliness & urgency (announcement = fresh, immediate info) • High cultural relevance (major national event, high engagement potential) • Religious-cultural salience in national life (religious events) • Emotional resonance (joy, excitement, anticipation) • Supporting videos • Provide hashtags • Source by popular private media company (high followers)	• Timeliness & urgency • Cultural & Social Relevance • Religious events • Emotional tone • Supporting videos • Provide hashtags and keywords • Source by popular private media company	• Timeliness & urgency • Local & cultural relevance • Positive emotional tone • Religious sensitivity • Supporting videos • Trending hashtags and keywords • Source by popular private media company

the research question [103]. Any data segment that could help address the research questions should be coded. As coding progresses through repeated rounds of familiarization and refinement, it is possible to identify which codes are useful for interpreting themes and which ones might be discarded.

This iterative process is carefully documented, showing how codes evolve over time and how initial ideas grow into possible themes. Keeping track of this progression improves transparency and offers signposts for revisiting specific codes, if necessary, especially when certain approaches don't produce useful insights. The outcome produced from this phase was a preliminary set of descriptive and interpretive codes (preliminary coding), serving as the foundation for further analysis. Table 4 shows a sample of the tracking code changes during the preliminary coding process.

3) PHASE 3: GENERATING INITIAL THEMES

This phase involved reviewing and analyzing the codes generated in Phase 2. Following this, related codes were systematically grouped by shared meanings to form subthemes or themes. The themes should be distinct yet collectively coherent. Codes or potential themes that do not align can be discarded, and a miscellaneous category may be used for those that do not fit into any specific themes [102]. During the analysis process, we kept in mind that themes are not inherent in the data but rather are actively constructed by interpreting the relationships among codes. The significance of a theme resides not in the quantity of codes it encompasses, but rather in its capacity to represent meaningful patterns that address the research question. By the end of this phase, an initial thematic map was generated, presenting a draft list of candidate themes and subthemes.

4) PHASE 4: DEVELOPING AND REVIEWING THE THEMES

In this phase, potential themes and subthemes were iteratively reviewed, refined, and reorganized to maintain analytical flexibility and reflexivity, ensuring that the dataset's complexity was adequately captured while remaining aligned with the research objective [103]. It is quite common to discover that some candidate themes may lack meaningful interpretation of the data or fail to address the research question [102]. Additionally, some supporting codes and data items may be incongruent and require revision.

Two levels of review process were conducted to validate the correspondence between the assigned codes and their respective themes, as well as the relevance of themes to the interpretation of the dataset [92]. The first level involved examining the relationships among data items and codes within each candidate theme and subtheme. Where the items and codes formed a coherent pattern, the theme or subtheme was considered to present a logical argument that could contribute meaningfully to the overall narrative of the dataset. The second level focused on reviewing the candidate themes concerning the entire dataset, assessing how well they captured and represented the data in alignment with the research questions. Like other phases, all changes were documented to track the actions taken to produce a revised thematic map that highlights the most important elements of the data related to the research question. As a result, this phase produced the final version of the refined theme structure. At this stage, the refined themes were also checked against the ELM to ensure alignment with central and peripheral routes, while retaining their inductive grounding.

5) PHASE 5: REFINING, DEFINING, AND NAMING THE THEMES

This phase focused on presenting a detailed analysis of the developed themes. Each theme and subtheme were defined and named through a rigorous review process to ensure coherence with both the dataset and the research questions. To substantiate the analysis, data extracts were selected to capture the essence of each theme. These extracts were interpreted not only descriptively but also analytically, highlighting their broader significance within the dataset. Following Braun and Clarke's guidance, the extracts were used to illustrate and support analytic claims, and in the reporting of results, they are presented as supporting quotes from tweets, providing direct evidence of how the themes are grounded in the data [92], [94]. The naming of themes was then finalized to be concise, informative, and memorable, while remaining theoretically aligned with the ELM. This alignment allowed the themes to be meaningfully integrated with the study's conceptual model, bridging the data-driven insights with the theoretical framework. The outcome of this phase was a set of finalized themes with meaningful names, clear definitions, and tweet quotes.

6) PHASE 6: WRITING THE REPORT

In RTA, writing is not a separate stage but interwoven throughout the analysis. The final phase represents the refinement and completion of the report, where themes are presented in a coherent narrative form, supported by selected tweet quotes that illustrate each theme, and aligned to the research objective. In this study, theme reporting was guided not only by inductive meaning-making but also by alignment with the ELM. The excerpts were carefully chosen to exemplify how each theme aligns with either high or low cognitive processing factors. This phase integrated empirical evidence with theoretical insights to explain how specific information characteristics influence sharing behavior on the X platform. Researcher reflexivity was maintained, recognizing the interpretive nature of theme development and reporting. Care was taken to balance raw data, ELM constructs, and practical implications for misinformation interventions. Table 5 illustrates the final thematic framework mapping across phases, presenting the codes, themes, and subthemes with alignment to the ELM's dual-processing model.

D. TRUSTWORTHINESS AND ETHICAL CONSIDERATIONS

In line with Braun and Clarke's conceptualization of RTA, this study did not employ reliability metrics such as inter-coder agreement, as this is not compatible with the interpretivist orientation of RTA [93], [95]. Instead, rigor was ensured through a reflexive and transparent process. This included continuous reflexive documentation at each stage, such as taking preliminary notes in Phase 1 and conducting preliminary coding in Phase 2. This approach helped maintain transparency in the analytic process. Additionally, reflexive journaling documented the iterative process, recording changes and progress while allowing for a critical examination of the researcher's influence and positionality. Rich and detailed descriptions of themes were provided to ensure that interpretations were firmly grounded in the data. For ethical considerations, all tweets used in this study were publicly available, anonymized where appropriate, and handled in accordance with ethical standards for digital research. Data collection and analysis complied with X's public data terms of service, and only publicly accessible tweets were included.

IV. RESULTS

The findings of this study aim to identify the key information characteristics that influence information-sharing behavior on social media. Through RTA, five key themes were derived from the dataset of 92 viral tweets: Social Interest, Political Interest, Visual Appeal, Credible Sources, and Emotional Appeal. A detailed mapping of all tweets is provided in Appendix, offering additional context for understanding their distribution and substantiating the thematic classifications.

Building upon the ELM-informed RTA outlined in the methodology section, each theme is interpreted through the lens of the ELM's central-peripheral distinction. The analysis reveals that Social Interest and Political Interest align with the central route, as they demand higher levels of cognitive engagement and elaboration. By contrast, Visual Appeal, Credible Sources, and Emotional Appeal reflect the peripheral route, where information processing relies on heuristic cues or affective elements, requiring less cognitive effort. This thematic distribution illustrates how dual-processing mechanisms operate within viral tweets: cognitively demanding content attracts engagement through deliberation, while heuristic and emotional cues facilitate more immediate, peripheral processing. Table 6 summarizes the categorization of these themes in accordance with the ELM framework.

A. THEME 1: SOCIAL INTEREST

The Social Interest theme encompasses tweets that address significant societal challenges, including activism, culture, religious matters, public health, public conflict, and crisis responses. These topics typically require high cognitive engagement, as users must critically process the information to understand its implications. Within the ELM framework, this theme aligns with the central route, as individuals are motivated to engage deeply with personally relevant issues, a process that requires prior knowledge and reinforces the premise that motivation and ability are essential for central-route persuasion [49].

1) REPRESENTATIVE EXTRACT

"The 90th Anniversary of the Royal Malaysian Navy (TLDM) Day Parade scheduled to take place this Saturday, has been cancelled and replaced with a tahlil ceremony and doa selamat."

This tweet illustrates user engagement with socially sensitive information that demands contextual awareness. Familiarity with prior events allows users to interpret the change as a respectful act, exemplifying central-route processing where prior knowledge and critical reflection inform the interpretation and sharing of meaningful content.

The analysis revealed that tweets related to social topics, such as human rights violations, environmental concerns, and public safety matters, were widely shared. The nature of the tweet encourages deliberation, discussion, and awareness, fostering informed sharing behavior. This reflects users' motivation to engage with content that resonates with collective responsibility and societal well-being. Empirical research supports this assertion, indicating that socially relevant issues, including social justice and collective welfare, not only foster higher engagement levels but also stimulate

TABLE 5. Final thematic framework mapping across RTA phases.

Cognitive Level	ELM Theory Alignment	Phase 4 & Phase 5 - Themes	Phase 3 – Themes/Subthemes	Phase 2 – Codes
High	Central Route	Social Interest	Social Issues and Awareness	activism and advocacy broader social or national issues community support and awareness consumer advocacy tone environmental concerns human rights misinformation awareness obituary news public figure-related information moral responsibility and ethical conducts
			Crisis and Conflict	court cases disasters and accidents news geopolitical issues high-profile controversies interpersonal conflict in the public sphere public safety and crime
			Health and Welfare	health-related and outbreak child protection and welfare
			Cultural & Religious Relevance	local and cultural relevance religious sensitivity
			Timely & Urgent news	timeliness and urgency
		Political Interest	Politics and Governance	educational concerns focus on policy governance and economy concerns official announcement political tone royal commentary on public issues
	Peripheral Route	Emotional Appeal	Emotional and Inspirational Content	negative emotional appeal motivation, inspiration and achievement positive emotional tone novelty and uniqueness celebrity story humor and animals
		Credible Sources	Popular Accounts	source by popular government channel source by popular independent media source by popular private media company trending hashtags and keywords
			Credibility	personal credibility link to original source
		Visual Appeal	Visual Media	image label supporting images supporting video
Low			High Engagement	high score of like high score of retweet high score of view high score of reply

central processing, as individuals feel compelled to conduct a more profound evaluation of the arguments presented [61], [70], [79].

However, the potential for misinformation dissemination exists if this content is not critically assessed. This emphasizes the need for fact-checking initiatives, the promotion of critical thinking, and awareness campaigns to ensure that shared information is accurate, trustworthy, and beneficial to society.

B. THEME 2: POLITICAL INTEREST

The theme of Political Interest was another dominant category, covering topics related to governance, policies, and political discourse [60], [69]. These topics generally require substantial cognitive engagement, as users interpret complex arguments, evaluate competing viewpoints, and consider broader societal implications. Within the ELM framework, this theme aligns with the central route, where individuals are motivated to process political content deeply due to its perceived personal and societal relevance [49].

1) REPRESENTATIVE EXTRACT

"The government agreed to increase the minimum wage rate from RM1,500 per month to RM1,700 per month which will come into effect from 1 February 2025."

This tweet highlights how policy updates encourage analytical engagement, prompting individuals to reflect on past government decisions and their broader implications. Such content fosters critical thinking driven by political awareness and personal relevance, rather than mere reactions to surface cues.

The analysis revealed that tweets addressing controversial political decisions, parliamentary debates, and governance updates garnered high engagement, particularly when they elicited strong opinions or sparked debates among users. It is widely recognized that political discussions often require users to interpret complex arguments, assess credibility, and form informed opinions, thereby reinforcing their engagement through rational deliberation and critical thinking. Recent findings further indicate that issue involvement and political alignment play a central role in shaping such engagement through central processing, as individuals are particularly motivated to scrutinize arguments and evaluate credibility when the content reinforces their political stance or challenges their beliefs [60].

However, the presence of ideological biases and polarized discussions within political content may lead to misinformation risks [60], [104], further underscoring the importance of platform nudging and fact-checking initiatives to prevent misleading narratives from influencing public perception. Social media platforms could implement verification labels, misinformation alerts, or political fact-checking tools to promote informed sharing behavior in politically sensitive discussions.

C. THEME 3: VISUAL APPEAL

The Visual Appeal theme underscores the crucial role that images, videos, and other multimedia elements play in influencing information-sharing behavior. Such cues reduce the need for deep cognitive engagement, prompting users to make faster, less analytical judgments about what content to share. Within the ELM framework, this theme is situated under the peripheral route, where decisions are guided less by rational deliberation and more by heuristic cues such as vividness, attractiveness, and media richness [52].

As illustrated in Fig. 4, the tweet uses a compelling visual element to capture attention and provoke immediate, affect-driven reactions, prompting quick judgments without deep cognitive processing.

The analysis revealed that tweets featuring eye-catching visuals, such as compelling images, infographics, or videos, consistently garnered more engagement than those that relied solely on text. This demonstrates the effectiveness of visual stimuli in capturing user attention and encouraging shares. This observation aligns with previous research that emphasizes the strong effect of visual attractiveness and cues on user attention and the virality of tweets on social media, as these elements can stimulate peripheral processing and enhance engagement [27], [70], [85], [105].

While visuals enhance engagement, this type of tweet also increases the risk of spreading misinformation, as users are often misled by its aesthetic appeal rather than its factual accuracy. For this reason, intervention strategies can include heuristic cues, such as image verification prompts and AI-powered authenticity checks, to motivate users to evaluate the credibility of visual content before sharing it.

FIGURE 4. Representative extract for visual appeal theme.

D. THEME 4: CREDIBLE SOURCES

The Credible Sources theme emphasizes the crucial role of source credibility as a heuristic shortcut in the process of information-sharing, situating it within the peripheral route of the ELM. This aligns with the peripheral route of ELM, where credibility serves as a cognitive shortcut, enabling individuals to make quick decisions without requiring in-depth processing [52].

1) REPRESENTATIVE EXTRACT

"The Malaysian Meteorological Department (MetMalaysia) informed that the transitional phase of the monsoon is expected to start on March 29 and continue until May.

Follow the latest news at https://grid.astroawani.com"

This tweet illustrates source credibility as a heuristic cue. Originating from an official agency and a reputable channel, it encourages quick acceptance without thorough evaluation, reflecting peripheral-route processing where credibility simplifies decision-making and enhances rapid information sharing.

The findings revealed that tweets from government agencies, reputable outlets, and independent media organizations were frequently shared, indicating that users often rely on the source's reputation as a heuristic shortcut instead of critically evaluating the content. This aligns with previous studies that indicate credible sources are typically identified through the peripheral route, where individuals quickly assess the credibility of information as a shortcut to conserve cognitive energy and time, ultimately influencing their trust and decisions about sharing [30], [61], [78], [80], [106].

However, while this practice builds trust in verified information, it can also create a blind dependence on authority, allowing misinformation from seemingly credible sources to spread unchecked [107]. For this reason, the importance of

TABLE 6. The 5 themes identified from the data analysis.

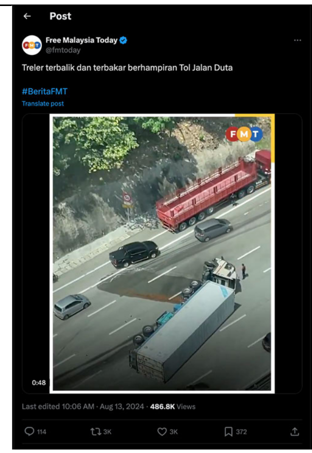
Theme	Description	ELM Processing Route	Justification of ELM Processing Route	Sample tweet	References
Social Interest	Content related to information addressing societal challenges, including activism, culture, religious matters, public health, public conflict, and crisis responses.	Typically processed via Central Route (when cognitive in motivation & ability are high)	Social interest content requires high cognitive engagement as users demand critical evaluation and collective awareness to process and evaluate the information. This aligns with the central route as individuals are motivated to process content deeply due to personal relevance and societal responsibility.	"The parents of the late Zulfarhan Osman Zulkarnain prostrated in gratitude after the judge announced the death sentence for all six accused." "Three outbreak areas have also been declared in Kelantan, namely in Tanah Merah, Pasir Puteh and the latest in Kota Bharu on March 14." "[LATEST] Firefighters confirm landslide in front of Masjid India, rescue work for trapped victims is underway."	[49], [61], [70], [79]
Political Interest	Content related to political discussions, governance, policies, and breaking developments.	Typically processed via Central Route (when cognitive in motivation & ability are high)	Political interest content requires high cognitive engagement as users interpret complex arguments, assess credibility, and evaluate societal implications. This aligns with the central route, where individuals are motivated to scrutinize political information deeply due to its personal and societal relevance.	"You have to give the right example. Read it first. Don't read it directly to make a perception... If I didn't 'check' earlier, 'you' would have taken away TikTok, one Malaysia has entered...," said YB Bangi, Syahredzan Johan." "Controversy over Anwar's appointment as PM, Tengku Hassanal urged the police to take action against Muhyiddin." "The cancellation of pensions also applies to elected representatives, said the PM."	[49], [60], [69]
Visual Appeal	Tweets with strong visual elements, such as images and videos, that enhance engagement.	Typically processed via Peripheral Route (when cognitive in motivation & ability are low, relying on affective and heuristic cues).	Visual appeal such as images and videos encourages low cognitive processing, prompting heuristic judgments. This reflects the peripheral route, where engagement is guided by vividness, attractiveness, and media richness rather than critical evaluation.		[27], [52], [70], [85], [105]

TABLE 6. *(Continued.)* **The 5 themes identified from the data analysis.**

Credible Sources	Content from verified or authoritative sources, including government agencies and independent media.	Typically processed via Peripheral Route (when cognitive in motivation & ability are low, relying on affective and heuristic cues).	Credible sources encourage low cognitive processing through heuristic shortcuts, as users rely on reputation, trustworthiness, authority, and popularity rather than critically evaluating content. This aligns with the peripheral route, where credibility acts as a shortcut that enables quick judgments, conserving effort while shaping trust and sharing decisions.		[52], [61], [30], [78], [80], [106]
Emotional Appeal	Content that primarily evokes emotional reactions from audiences, which can influence engagement and sharing behavior on social media. This theme includes both positive and negative emotional triggers, such as humor, inspiration, motivation, novelty, and sentiments of sadness or tragedy.	Typically processed via Peripheral Route (when cognitive in motivation & ability are low, relying on affective and heuristic cues).	Emotional appeal encourages low cognitive processing as users rely on affective cues such as humor, sadness, novelty, or inspiration rather than analytical evaluation. This aligns with the peripheral route, where instant emotional impact drives engagement and sharing, often overshadowing critical thinking and influencing decision-making.	"Malaysia leads the world in the use of mobile wallets, with 63 percent of Malaysians using the facility to shop, said global financial technology platform Adyen. This is the highest usage rate worldwide, according to the Adyen Index 2024, a survey based on retail reports of over 38,000 shoppers as well as 13,000 merchants in 26 markets including over 1,000 consumers and 500 businesses in Malaysia, conducted from 15 Jan to 1 Feb 2024." " 'I had no sons when they both died in an accident.' That was the statement of Jamaludin Hussin, the father of one of the three Universiti Teknologi Mara (UiTM) Dungun students who died in a road accident in Kuala Terengganu last night." " 'Crazy work succeeded', 3 young Malaysians built the world's first wireless charging station."	[27], [49], [71], [73], [77]

diverse information exposure, media literacy programs, and digital verification tools that encourage users to critically assess information, even when it comes from trusted sources, is crucial. Encouraging cross-verification across multiple sources and implementing AI-driven credibility ratings could further improve responsible information-sharing behavior.

E. THEME 5: EMOTIONAL APPEAL

The final theme, Emotional Appeal captures tweet that evokes strong affective responses, influencing user engagement and information-sharing behavior on social media. It includes both positive and negative emotional triggers such as humor, motivation, inspiration, novelty, sadness, and tragedy. Despite limited cognitive evaluation, emotionally charged content often garners widespread attention and is highly shareable due to its instant emotional impact. Within the ELM framework, this theme aligns with the peripheral route of processing in the ELM, where users are guided more by affective cues like emotional tone, relatability, or entertainment value than by analytical scrutiny [49].

1) REPRESENTATIVE EXTRACT

"78-year-old woman robbed in Bangsar [anonymized public tweet containing video footage]."

This tweet demonstrates how emotionally charged content accompanied by video evidence can evoke empathy and concern, leading to quick engagement and sharing without much analysis. These responses reflect peripheral-route processing, where emotional appeal acts as a shortcut cue, prompting users to accept and spread the information rapidly.

The findings revealed that tweets featuring personal achievements, heartwarming stories, viral trends, or celebrity moments are commonly shared not because of their factual depth, but because they resonate emotionally and fulfill users' social validation needs. Empirical literatures indicate that emotional cues can significantly influence behavior through the peripheral route by evoking feelings such as empathy, anger, or excitement, which often overshadow critical thinking and alter decision-making processes [27], [71], [73], [77]

However, the emotionally driven nature of such content increases the risk of unverified or sensationalized narratives spreading, especially when users bypass critical assessment. This concern is particularly relevant in misinformation, as emotionally appealing falsehoods tend to spread faster than factual content [108]. To address this, platforms can implement emotion-based misinformation warnings, AI-driven prompts to encourage reflective sharing, and digital literacy campaigns that help users recognize the distinction between emotionally engaging but misleading content and accurate, fact-based information.

V. DISCUSSION

The study's findings enhance understanding of how information characteristics influence information-sharing behavior on social media. This methodological approach allowed not only the identification of patterns in the data but also the acknowledgment of the active role of researchers in knowledge construction and theme development throughout the analytical process. The identified characteristics provide valuable criteria that could guide stakeholders, including policymakers, social media platforms, educators, and individual users, in designing effective intervention strategies to mitigate misinformation on social media.

The analysis reveals that Malaysian viral tweets are primarily driven by topic interest, visual appeal, and the credibility of sources. Content that addresses social issues, political interests, and emotional appeals tends to garner the most shares, likely because these topics resonate with national concerns and trends in Malaysian society. Furthermore, tweets that include videos or images play a significant role in spreading information, as they offer compelling evidence that can elicit emotional responses and build trust, motivating users to share. Meanwhile, credible sources offer a cognitive shortcut, enabling individuals to accept information from trusted channels, which often leads to virality.

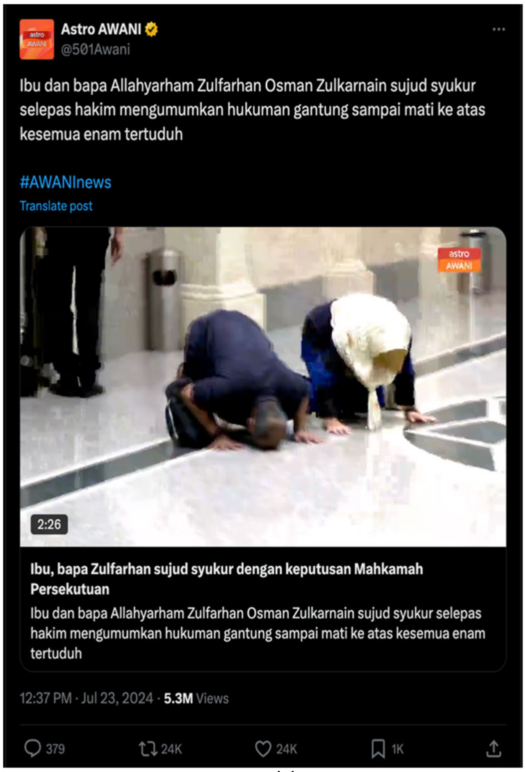
To address the research question, "What are the characteristics of information that influence information-sharing behavior on social media?", three illustrative case studies were presented. These case studies were selected to demonstrate how different information characteristics operate within the ELM framework, showcasing how content triggers central, peripheral, or mixed processing. By analyzing real examples of viral tweets through RTA, a better understanding of the practical manifestation of these theoretical concepts and their influence on sharing behavior can be developed.

A. CASE STUDY 1

These examples represent tweets under the Social Interest theme that became viral in Malaysia in 2024. Both pieces of information included videos (Visual Appeal theme) and were shared by Astro Awani, a credible source (Credible Sources theme). This combination of characteristics contributed to their significant virality. Analyzing how these tweets were processed according to ELM theory reveals important distinctions in cognitive processing routes.

Fig. 5(a) case study example requires prior knowledge of the case, suggesting alignment with the central processing route, where individuals need background information to meaningfully engage with and share the content. Evidence of this appears in user replies, which demonstrate familiarity with the case background. A comment noted: "That's the way to deal with this type of extreme bullies. Well done to the judge. Hopefully, no reversal." Although the tweet incorporates visual elements and comes from a credible source, central processing appears to be the dominant factor in users' decisions to share this information.

Fig. 5(b) case study example announces the Eid celebration date for Muslims in Malaysia. This information holds personal relevance primarily for Muslim Malaysians, creating motivation to share with others. This example also aligns



(a)
Tweet on "The mother and father of Allahyarham Zulfarhan Osman Zulkarnain bowed in gratitude after the judge announced the death sentence on all six accused"

(b)
Tweet on "Eid tomorrow!!! Hari Raya Aidilfitri for all states is declared throughout Malaysia on Wednesday 10 April 2024"

FIGURE 5. Social interest tweet examples.

with central processing, as those who shared were likely anticipating this announcement and possessed contextual knowledge about Eid celebrations. Despite the presence of video content and a credible source, the personal relevance aspect of central processing seems to be the primary driver behind sharing behavior.

In conclusion, these findings underscore the role of topic interest, credibility, and visual appeal in driving the virality of social media content in Malaysia. While both case study examples incorporated peripheral cues such as videos and trusted sources, the central route of processing played a dominant role, as individuals engaged with and shared the tweets based on prior knowledge, issue familiarity, and personal relevance. Understanding these patterns is crucial for designing effective intervention strategies to combat misinformation, as it highlights the importance of tailoring content to users' cognitive engagement levels and information-processing tendencies.

B. CASE STUDY 2

These examples exemplify tweets categorized under the Political Interest theme that gained significant traction in Malaysia during 2024. Both tweets address the same policy announcement but were disseminated through different news channels: Astro Awani (see Fig. 6(a)) and Free Malaysia Today (see Fig. 6(b)), respectively. While both generated substantial user engagement, Astro Awani's tweet demonstrated markedly higher engagement metrics (views and retweets), likely attributable to its status as a regulated corporate entity subject to Malaysian media legislation, enhancing its perceived credibility among the audience.

The incorporation of visual elements (video in Astro Awani's case and image in Free Malaysia Today's) strengthened the perceived reliability of the content, consequently facilitating increased sharing behavior. Analyzing these examples through the lens of the ELM reveals that processing such information necessitates cognitive engagement, particularly among individuals with a vested interest in Malaysian political developments. This suggests alignment with the central processing route of persuasion. However, it is noteworthy that peripheral cues such as visual components and source credibility significantly bolstered sharing decisions. This is evidenced by Astro Awani's superior engagement metrics, which can be attributed to its effective use of video content that provides stronger evidence, along with its established reputation as a credible information source.

The case study illustrates the interplay between central and peripheral processing routes in the diffusion of information on social media platforms. While substantive content can trigger cognitive processing, peripheral elements can significantly enhance sharing behavior. The differing engagement metrics between these tweets, which report the same

(a)
Tweet on "The Prime Minister, Datuk Seri Anwar Ibrahim said that all new appointments of civil servants will not have pensions and the same goes for new appointments of politicians"

(b)
Tweet on "The cancellation of pensions also applies to elected representatives, said the PM"

FIGURE 6. Political interest tweet examples.

information, highlight the essential role of source credibility and how content is presented in information dissemination, despite the core message being constant. For this reason, it is significant to understand how peripheral cues can enhance the dissemination of political information in digital environments, potentially serving as entry points for deeper engagement with the content itself.

C. CASE STUDY 3

These examples represent tweets categorized under the Emotional Appeal theme that achieved viral status in Malaysia in 2024. Both tweets incorporated images that enhanced visual engagement and emotional impact for audiences. When analyzed through the ELM framework, these examples demonstrate distinct processing characteristics compared to previously examined cases.

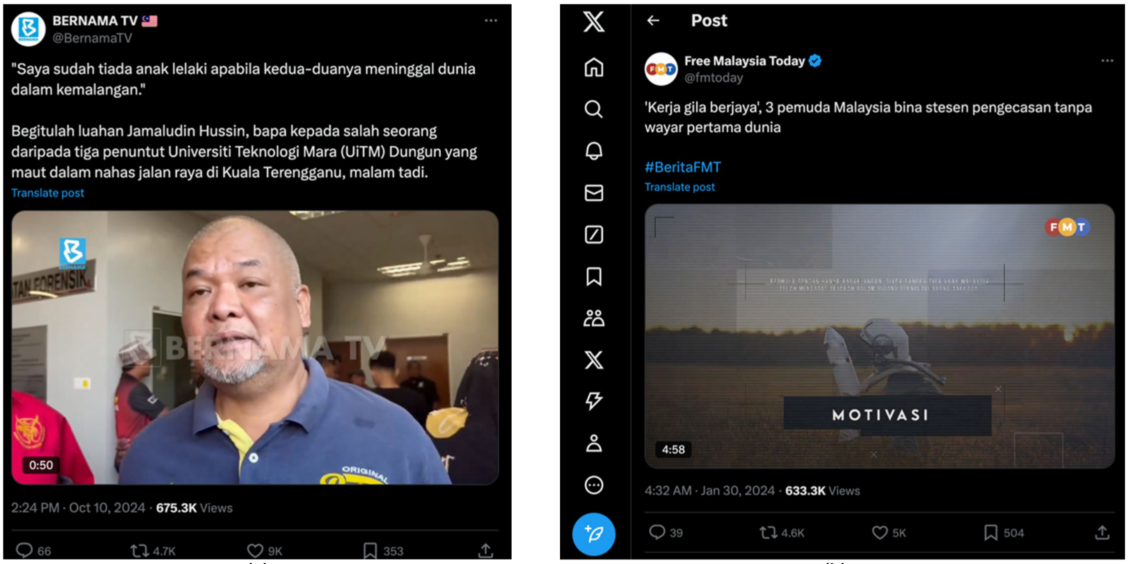
Unlike content requiring substantive prior knowledge, these emotional appeal tweets facilitate information processing through the peripheral route. The first tweet about an accident evokes profound sadness and empathy through the father's paradoxical statement, creating a strong emotional connection that motivates sharing as an expression of collective grief (see Fig. 7(a)). The second tweet about wireless charging innovation taps into positive emotional responses of national pride and celebration of achievement, appealing to aspirational values and collective identity (see Fig. 7(b)).

The visual elements in both tweets serve as significant peripheral cues that amplify emotional impact and lower the threshold for sharing behavior. These images function not merely as supplementary content but as critical persuasive elements that facilitate rapid emotional connection with the material.

This case study illustrates how emotional appeal, both through tragedy and triumph can effectively drive viral sharing when content triggers strong emotional responses that resonate with fundamental human experiences and values. The combination of emotionally resonant content with visual elements creates optimal conditions for peripheral processing and subsequent sharing behavior. These findings suggest that content creators seeking engagement with Malaysian audiences may effectively leverage both positive and negative emotional appeals, presented with strong visual components, to maximize sharing potential through peripheral route processing.

1) THE ROLE OF INFORMATION CHARACTERISTICS IN THE COGNITIVE PROCESSING CONTINUUM

This subsection will comprehensively explore the key findings of information characteristic themes identified through RTA, along with an analysis of illustrative case studies from the perspective of the ELM cognitive processing continuum. As mentioned earlier, the ELM outlines dual-process modes: the central route (high elaboration) and the peripheral route (low elaboration), representing points on an elaboration continuum that illustrates how individuals process the information they encounter. As outlined in the literature review,



(a)
Tweet on " 'I had no sons when they both died in an accident.' That was the statement of Jamaludin Hussin, the father of one of the three Universiti Teknologi Mara (UiTM) Dungun students who died in a road accident in Kuala Terengganu last night."

(b)
Tweet on " 'Crazy work succeeded', 3 young Malaysians built the world's first wireless charging station"

FIGURE 7. Emotional appeal tweet examples.

individuals with high cognitive engagement usually process information through the central route, whereas those with lower engagement often follow the peripheral route. However, a moderate zone of elaboration exists between these two extremes, where both heuristic cues and systematic processing influence decision-making [57], [58]. In this intermediate space, users may first rely on peripheral cues for quick evaluations before delving into a thorough cognitive assessment when the content appears particularly relevant or personally meaningful. The analysis of illustrative case studies collectively addresses the research question by demonstrating that information characteristics influence sharing behavior through various cognitive processing routes. This finding aligns with previous studies, which indicate that cognitive processing interactions suggest that persuasion outcomes rarely manifest as solely central or peripheral [57], [58]. Instead, they are a dynamic blend shaped by user engagement, prior knowledge, and contextual elements.

The cognitive processing continuum emphasizes that information processing occurs on a spectrum rather than in fixed categories. Users shift between different processing levels based on factors like content salience, personal relevance, source credibility, and visual cues. For example, when content is personally relevant or socially salient, such as social issues or political topics, it often prompts deeper engagement and more deliberate processing via the central route. In contrast, elements such as visual appeal and source credibility can influence users across various cognitive processing levels. The prevalence of mixed processing highlights the importance of a hybrid approach to content engagement, where appealing elements are paired with meaningful content, promoting more thoughtful and informed sharing behavior. Notably, the case studies illustrate that many viral tweets engage mixed processing channels, with both central and peripheral factors influencing sharing choices.

To clarify the discussion, Fig. 8 illustrates how information characteristics influence the cognitive processing continuum within the ELM framework, specifically in relation to information-sharing behavior on social media. It emphasizes the continuum of cognitive processing, reflecting the various levels of cognitive motivation and ability that individuals exhibit when engaging with information. Three processing levels were identified, including central processing, peripheral processing, and mixed processing.

The role of central processing is evident in Case Studies 1 and 2, where cognitive involvement, characterized by high motivation and ability, dominates information processing. As observed in the results section, the themes of Social Interest and Political Interest align with the central route that demands deep processing when the content involves major public discourse. Both case studies provide supporting evidence for this, highlighting how issue-relevant thinking is triggered by complex, context-dependent information. For instance, the tweet on judicial sentencing in Case Study 1 required users to have prior knowledge of the case, whereas the tweets in Case Study 2, concerning pension reforms for civil servants and politicians, prompted users to reflect on broader political developments in Malaysia. Even when confronted with complex arguments, users may participate in issue-relevant thinking, forming opinions based on prior knowledge and a broader contextual understanding.

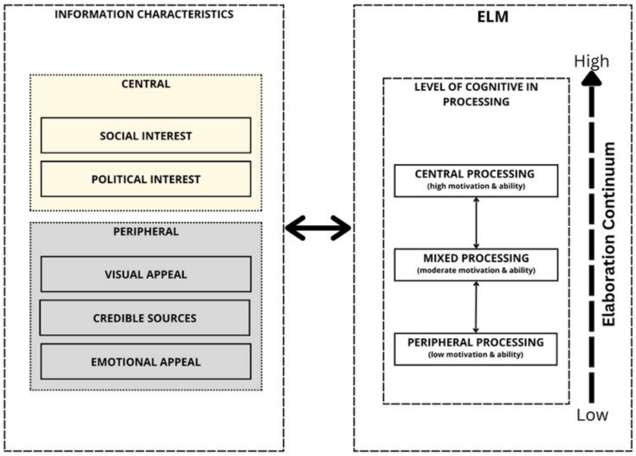


FIGURE 8. The influence of information characteristics in cognitive processing continuum of the ELM framework.

The influence of peripheral processing on information sharing is evident in Case Study 3, where low motivation and ability are involved due to the affective and heuristic cues that facilitate quick decision-making. This case highlights how tweets about the tragic accident involving university students and Malaysian technological innovation gained widespread attention through emotionally charged and visually compelling content. Users were drawn to these narratives and shared them with minimal cognitive effort, largely driven by emotions such as empathy, grief, national pride, and the positive affect elicited by visuals.

Despite the presence of peripheral cues, deeper processing is not inherently excluded, nor does it automatically diminish the significance of these cues. When cognitive involvement is at a moderate level, characterized by balanced motivation and ability, various modes of processing can be utilized concurrently. The analyzed case studies reveal that information processing rarely follows a single path. For instance, Case Study 1's tweet about the Eid announcement engaged central processing through its personal relevance to Muslims, while being further enriched by peripheral factors such as video content and the credibility of the source. In Case Study 2, although the pension policy required central processing, peripheral elements such as video and source credibility significantly amplified information-sharing behavior. Additionally, Case Study 3 illustrates that emotional and visual components can initially serve as captivating heuristics, encouraging users to engage more deeply and leading to central route processing. The interaction between peripheral and central routes demonstrates that emotional engagement and visual attractiveness can effectively capture user attention and encourage more in-depth evaluations. This enhances the credibility of messages and fosters the sharing of information. It exemplifies the real-world application of mixed processing, where users combine both central and peripheral aspects depending on contextual elements, such as the complexity of the content, individual interests, and time constraints.

2) FROM THEORY TO PRACTICE: MISINFORMATION INTERVENTION STRATEGIES PERSPECTIVE

From an intervention perspective, the case studies provide essential insights for developing targeted strategies to promote responsible information-sharing behavior on social media. These strategies should incorporate components from various levels of cognitive engagement to address all types of tweets effectively. As the case studies demonstrate, tweets combine numerous characteristics, such as social interest and visual appeal, which may trigger both central and peripheral processing routes. This reinforces the need for hybrid-based intervention strategies that simultaneously address deeper cognitive engagement and surface-level heuristic cues [109]. To enhance practical value, actionable recommendations can be delineated across several stakeholder groups: policymakers, social media platforms, educators, and individual users.

For policymakers, the findings highlight the urgent need to strengthen media regulations by establishing clearer policies that require transparency in platform algorithms (theme: Credible Sources). Additionally, it is crucial to develop campaigns aimed at increasing citizens' awareness of the importance of critically evaluating viral political and social content (themes: Political Interest; Social Interest), especially when it includes emotional or visual elements (themes: Emotional Appeal; Visual Appeal). This combined strategy can reinforce regulatory frameworks while promoting essential media literacy, empowering individuals to navigate the complexities of today's media landscape.

Social media platforms, as key stakeholders, have a substantial influence on information-sharing behavior due to credibility cues and visual appeal. To address this, platforms should implement contextual credibility markers (themes: Credible Sources; Visual Appeal), such as tags for "verified news outlets" and fact-checking overlays, particularly during heightened political and social discourse (themes: Political Interest; Social Interest). Additionally, prioritizing credible sources like Bernama or Awani through algorithmic adjustments during national events can help mitigate misinformation (themes: Credible Sources; Political Interest; Social Interest). These measures would enhance the platforms' responsibility in fostering an informed public.

Educators can leverage these findings to develop media literacy programs that address both the central and peripheral processing routes identified in this research (themes: Social Interest; Political Interest; Emotional Appeal; Visual Appeal). Training should focus not only on fostering fact-checking practices but also on enhancing awareness of the ways in which emotional and visual appeals (themes: Emotional Appeal; Visual Appeal) can circumvent critical thinking processes.

Finally, individual users represent a critical starting point in addressing the challenges of misinformation in the digital landscape. By embracing a "pause-and-verify" approach before sharing viral content (themes: Credible Sources;

TABLE 7. Distribution of tweets to theme classification.

Tweet ID	A : Social Interest	B : Political Interest	C : Visual Appeal	D : Credible Sources	E : Emotional Appeal
1 : Awani 1	✓		✓	✓	✓
2 : Awani 2	✓		✓	✓	✓
3 : Awani 3	✓		✓	✓	✓
4 : Awani 4	✓		✓	✓	✓
5 : Awani 5	✓		✓	✓	✓
6 : Awani 6	✓		✓	✓	✓
7 : Awani 7	✓		✓	✓	
8 : Awani 8	✓		✓	✓	✓
9 : Awani 9	✓		✓	✓	
10 : Awani 10		✓	✓	✓	✓
11 : Awani 11	✓	✓	✓	✓	
12 : Awani 12	✓		✓	✓	✓
13 : Awani 13	✓		✓	✓	
14 : Awani 14	✓		✓	✓	✓
15 : Awani 15	✓	✓	✓	✓	
16 : Awani 16	✓		✓	✓	
17 : Awani 17	✓		✓	✓	
18 : Awani 18	✓		✓	✓	
19 : Awani 19	✓	✓	✓	✓	
20 : Awani 20	✓		✓	✓	
21 : Awani 21	✓		✓	✓	✓
22 : Awani 22		✓	✓	✓	
23 : Awani 23	✓		✓	✓	
24 : Awani 24	✓		✓	✓	✓
25 : Awani 25	✓		✓	✓	
26 : Awani 26	✓		✓	✓	
27 : Awani 27			✓	✓	✓
28 : Awani 28	✓	✓	✓	✓	
29 : Awani 29	✓		✓	✓	✓
30 : Awani 30	✓		✓	✓	✓
31 : Awani 31			✓	✓	✓
32 : Awani 32		✓	✓	✓	✓
33 : Awani 33	✓		✓	✓	✓
34 : Awani 34	✓		✓	✓	✓
35 : Awani 35	✓	✓	✓	✓	✓
36 : Awani 36	✓		✓	✓	✓
37 : Awani 37	✓	✓	✓	✓	✓
38 : Awani 38	✓		✓	✓	✓
39 : Awani 39	✓		✓	✓	
40 : Awani 40		✓	✓	✓	
41 : Awani 41	✓		✓	✓	
42 : Awani 42	✓		✓	✓	
43 : Awani 43	✓		✓	✓	
44 : Awani 44	✓	✓	✓	✓	
45 : Awani 45			✓	✓	✓
46 : Awani 46	✓	✓	✓	✓	
47 : Awani 47	✓		✓	✓	
48 : Awani 48	✓	✓	✓	✓	
49 : Awani 49	✓	✓	✓	✓	
50 : Awani 50	✓	✓	✓	✓	
51 : Awani 51	✓	✓	✓	✓	
52 : Awani 52	✓		✓	✓	✓

Visual Appeal), they can significantly curb the diffusion of misinformation. This practice not only encourages personal accountability but also contributes to a collective responsibility within online communities.

TABLE 7. *(Continued.)* Distribution of tweets to theme classification.

53 : Awani 53	✓		✓	✓	
54 : Awani 54		✓	✓	✓	
55 : Awani 55	✓		✓	✓	✓
56 : Awani 56	✓		✓	✓	✓
57 : Awani 57	✓	✓	✓	✓	
58 : Awani 58	✓		✓	✓	✓
59 : Awani 59	✓		✓	✓	
60 : Awani 60	✓		✓	✓	✓
61 : Bernama 1	✓		✓	✓	✓
62 : Bernama 2	✓		✓	✓	✓
63 : Bernama 3	✓		✓	✓	✓
64 : Bernama 4	✓		✓	✓	✓
65 : Bernama 5	✓		✓	✓	
66 : Bernama 6	✓		✓	✓	
67 : fmtoday 1			✓	✓	✓
68 : fmtoday 2	✓		✓	✓	✓
69 : fmtoday 3	✓		✓	✓	✓
70 : fmtoday 4			✓	✓	✓
71 : fmtoday 5	✓	✓	✓	✓	
72 : fmtoday 6	✓		✓	✓	
73 : fmtoday 7	✓		✓	✓	
74 : fmtoday 8	✓		✓	✓	
75 : fmtoday 9	✓	✓	✓	✓	
76 : fmtoday 10		✓	✓	✓	
77 : fmtoday 11	✓		✓	✓	
78 : fmtoday 12	✓		✓	✓	✓
79 : fmtoday 13	✓		✓	✓	✓
80 : fmtoday 14	✓	✓	✓	✓	
81 : fmtoday 15	✓	✓	✓	✓	
82 : fmtoday 16	✓		✓	✓	✓
83 : fmtoday 17	✓	✓	✓	✓	
84 : fmtoday 18	✓		✓	✓	✓
85 : fmtoday 19	✓		✓	✓	
86 : fmtoday 20	✓		✓	✓	
87 : fmtoday 21			✓	✓	✓
88 : fmtoday 22	✓	✓	✓	✓	
89 : fmtoday 23	✓		✓	✓	✓
90 : fmtoday 24	✓		✓	✓	
91 : fmtoday 25		✓	✓	✓	
92 : fmtoday 26	✓		✓	✓	

VI. CONCLUSION

This study identifies and examines five key characteristics of information that influence sharing behavior on social media platforms: Social Interest, Political Interest, Visual Appeal, Credible Sources, and Emotional Appeal. The study applies the ELM as a theoretical framework to analyze viral tweets from Malaysian news channels. Utilizing RTA, the research highlights how these factors impact the cognitive processing continuum that affects sharing decisions.

The findings demonstrate that information processing does not occur strictly through central or peripheral routes but instead along a flexible continuum influenced by motivation, ability, and contextual factors. Case studies reveal how central engagement (e.g., political or social issues) interacts with peripheral cues (e.g., visuals, credibility), underscoring the need for hybrid intervention strategies that address multiple levels of user engagement. For stakeholders, including policymakers, social media platforms, educators, and individual users, suggests the importance of designing interventions that combine media literacy (to foster deeper critical engagement), credibility markers (to support quick heuristic judgments), and platform-level safeguards (to address low-effort sharing behaviors).

This study has several important limitations that must be acknowledged. First, the dataset was intentionally restricted to 92 viral tweets collected from three prominent Malaysian news channels over 10 months. While this scope was appropriate for an in-depth qualitative thematic analysis [99], [100], the findings are context-specific and should not be assumed to generalize across other countries, media outlets, or social media platforms. Moreover, the dataset was unevenly distributed across the three channels, with more tweets derived from Astro Awani compared to Bernama TV and Free Malaysia Today. This imbalance might have affected the prominence of certain themes, as interpretive patterns could mirror Awani's communication style more strongly. However, such variation remains acceptable within a qualitative framework that favors conceptual depth over numerical balance. Second, this study did not account for the algorithmic operations of social media platforms, such as ranking, content curation, and recommendation systems. These mechanisms significantly shape visibility and engagement, often amplifying certain narratives while suppressing others. In addition to algorithmic influence, limiting the dataset to news channels rather than ordinary users may have influenced which peripheral cues were most visible. As a result, the virality of the tweets analyzed here may have been partly influenced by algorithmic prioritization rather than purely by user-driven sharing decisions. Finally, while the use of RTA enabled rich conceptual insights, it is interpretive in nature and reflects the researcher's analytical lens. Although reflexive practices were employed to ensure transparency, the findings are not intended for statistical generalization but rather for generating transferable analytical insights.

Future studies should explore the "mixed processing" phenomenon revealed in this research, in which information traits trigger both central and peripheral processing routes concurrently. This intermediate area on the cognitive processing spectrum necessitates detailed empirical scrutiny to clarify how users combine different processing methods when faced with complex information. In particular, experimental and cross-platform research could examine how platform algorithms interact with information characteristics to influence virality, and whether cultural or contextual factors influence shifts along the processing continuum. By enhancing the understanding of various processing mechanisms and their empirical expressions across different contexts, future research can foster more nuanced theoretical models and more efficient strategies for ensuring information integrity in ever-evolving digital information landscapes.

DATA AVAILABILITY

The dataset supporting the findings of this study is publicly available at DOI: [10.21227/fgn0-g759].

APPENDIXES

APPENDIX A

DISTRIBUTION OF TWEETS TO THEME CLASSIFICATION

See Table 7.

REFERENCES

[1] B. Yang, R. Zhang, X. Cheng, and C. Zhao, "Exploring information dissemination effect on social media: An empirical investigation," *Pers. Ubiquitous Comput.*, vol. 27, no. 4, pp. 1469–1482, Aug. 2023, doi: 10.1007/s00779-023-01710-7.

[2] N. Thompson, X. Wang, and P. Daya, "Determinants of news sharing behavior on social media," *J. Comput. Inf. Syst.*, vol. 60, no. 6, pp. 593–601, Nov. 2020, doi: 10.1080/08874417.2019.1566803.

[3] Z. Amin, N. M. Ali, and A. F. Smeaton, "Attention-based design and user decisions on information sharing: A thematic literature review," *IEEE Access*, vol. 9, pp. 83285–83297, 2021, doi: 10.1109/ACCESS.2021.3087740.

[4] G. Pennycook and D. G. Rand, "Lazy, not biased: Susceptibility to partisan fake news is better explained by lack of reasoning than by motivated reasoning," *Cognition*, vol. 188, pp. 39–50, Jul. 2019, doi: 10.1016/j.cognition.2018.06.011.

[5] Z. Amin, N. Mohamad Ali, and A. F. Smeaton, "Attention-based design and selective exposure amid COVID-19 misinformation sharing," in *Human–Computer Interaction. Design and User Experience Case Studies* (Lecture Notes in Computer Science), vol. 12764. Cham, Switzerland: Springer, 2021, pp. 501–510, doi: 10.1007/978-3-030-78468-3_34.

[6] B. Knutson, T. W. Hsu, M. Ko, and J. L. Tsai, "News source bias and sentiment on social media," *PLoS ONE*, vol. 19, no. 10, Oct. 2024, Art. no. e0305148, doi: 10.1371/journal.pone.0305148.

[7] M. Blankenship and M. Blankenship. (2020). *How Misinformation Spreads Through Twitter*. Accessed: Jan. 21, 2025. [Online]. Available: https://digitalscholarship.unlv.edu/

[8] Malaysian Communications and Multimedia Commission. (2022). *Internet Users Survey 2022 Malaysia*. Accessed: Jan. 21, 2025. [Online]. Available: http://www.mcmc.gov.my

[9] N. Newman, R. Fletcher, K. Eddy, C. T. Robertson, and R. K. Nielsen, "Digital news report 2023," Reuters Institute for the Study of Journalism, Oxford, U.K., Tech. Rep. RISJ-P6ES-HB13, 2023, doi: 10.60625/risj-p6es-hb13.

[10] (Jul. 2, 2024). *MCMC Conducts Ethics of Social Media Use Briefings To Enhance Digital Literacy*. Accessed: Jan. 21, 2025. [Online]. Available: https://www.bernama.com/en/news.php?id=2313639

[11] Y. A. Jasim, M. G. Saeed, and M. B. Raewf, "Analyzing social media sentiment: Twitter as a case study," *Adv. Distrib. Comput. Artif. Intell. J.*, vol. 11, no. 4, pp. 427–450, Jun. 2023, doi: 10.14201/adcaij.28394.

[12] K. K. Kapoor, K. Tamilmani, N. P. Rana, P. Patil, Y. K. Dwivedi, and S. Nerur, "Advances in social media research: Past, present and future," *Inf. Syst. Frontiers*, vol. 20, no. 3, pp. 531–558, Jun. 2018, doi: 10.1007/s10796-017-9810-y.

[13] T. Elmas, S. Stephane, and C. Houssiaux, "Measuring and detecting virality on social media: The case of Twitter's viral tweets topic," in *Companion Proc. ACM Web Conf.*, Apr. 2023, pp. 314–317, doi: 10.1145/3543873.3587373.

[14] I. Kennedy, M. Wack, A. Beers, J. S. Schafer, I. Garcia-Camargo, E. S. Spiro, and K. Starbird, "Repeat spreaders and election delegitimization," *J. Quant. Description, Digit. Media*, vol. 2, pp. 1–49, Jun. 2022, doi: 10.51685/jqd.2022.013.

[15] D. K. Han. (2020). *Predicting Influencer Virality on Twitter*. Accessed: Jan. 24, 2025. [Online]. Available: https://digitalcommons.dartmouth.edu/senior_theses

[16] C. E. M.-Sifuentes, J. Angel, G. Sidorov, O. Kolesnikova, and A. Gelbukh, "Virality prediction for news tweets using RoBERTa," in *Advances in Soft Computing (MICAI)* (Lecture Notes in Computer Science), vol. 13068, I. Batyrshin, A. Gelbukh, and G. Sidorov, Eds., Cham, Switzerland: Springer, 2021, doi: 10.1007/978-3-030-89820-5_7.

[17] K. Garimella and R. West. (2019). *Hot Streaks on Social Media*. Accessed: Jan. 24, 2025. [Online]. Available: https://www.aaai.org

[18] V. P. Singh, "Entropy theory of hydrologic systems," *J. Hydrologic Eng.*, vol. 29, no. 6, Dec. 2024, Art. no. 4024039, doi: 10.1061/jhyeff.heeng-6259.

[19] S. Skempton, "The informational fallacy in the philosophy of consciousness," *Phil. Forum*, vol. 50, no. 4, pp. 455–484, Dec. 2019, doi: 10.1111/phil.12238.

[20] R. Savolainen, "Elaborating the sensory and cognitive-affective aspects of information experience," *J. Librarianship Inf. Sci.*, vol. 52, no. 3, pp. 671–684, Sep. 2020, doi: 10.1177/0961000619871595.

[21] S. Fak-on and B. Chobthamdee, "A study of learning achievement using social media and digital video of students in the faculty of education," in *Proc. 5th Int. STEM Educ. Conf. (iSTEM-Ed)*. NY, USA: IEEE, Nov. 2020, pp. 63–65, doi: 10.1109/ISTEM-ED50324.2020.9332608.

[22] X. Lin, S. Sarker, and M. Featherman, "Users' psychological perceptions of information sharing in the context of social media: A comprehensive model," *Int. J. Electron. Commerce*, vol. 23, no. 4, pp. 453–491, Oct. 2019, doi: 10.1080/10864415.2019.1655210.
[23] L. Marin, "Three contextual dimensions of information on social media: Lessons learned from the COVID-19 infodemic," *Ethics Inf. Technol.*, vol. 23, no. S1, pp. 79–86, Nov. 2021, doi: 10.1007/s10676-020-09550-2.
[24] S. Munusamy, K. Syasyila, A. A. H. Shaari, M. A. Pitchan, M. R. Kamaluddin, and R. Jatnika, "Psychological factors contributing to the creation and dissemination of fake news among social media users: A systematic review," *BMC Psychol.*, vol. 12, no. 1, Nov. 2024, Art. no. 673, doi: 10.1186/s40359-024-02129-2.
[25] K. El Hedhli and H. Zourrig, "Dual routes or a one-way to persuasion? The elaboration likelihood model versus the unimodel," *J. Marketing Commun.*, vol. 29, no. 5, pp. 433–454, Jul. 2023, doi: 10.1080/13527266.2022.2034033.
[26] Z. Jiang, B. Wang, D. Cheng, F. Lou, and Z. Wang, "The effects of source credibility and content objectivity on pro-environmental post engagement on social media: A case study of Chinese TikTok (Douyin)," *Asian J. Social Psychol.*, vol. 28, no. 1, Mar. 2025, Art. no. e70002, doi: 10.1111/ajsp.70002.
[27] J. Fernandes and S. Segev, "The persuasion cues that make video advertising go viral: A conceptual replication and extension comparing viral vs. non-viral advertising," *J. Marketing Commun.*, pp. 1–27, Jul. 2024, doi: 10.1080/13527266.2024.2376918.
[28] S. Zhang, Y. Zhang, J. Li, Z. Ni, and Z. Liu, "Heart or mind? The impact of congruence on the persuasiveness of cognitive versus affective appeals in debunking messages on social media during public health crises," *Comput. Hum. Behav.*, vol. 154, May 2024, Art. no. 108136, doi: 10.1016/j.chb.2024.108136.
[29] J. Li, K. Zhu, and J. Jang, "Factors influencing users' content sharing intention in travel-related consumer generated media," in *Proc. ENTER22 E-Tourism Conf.*, Cham, Switzerland. Springer, 2023, pp. 113–127, doi: 10.1007/978-3-031-25752-0_13.
[30] H. Luo, X. Meng, Y. Zhao, and M. Cai, "Exploring the impact of sentiment on multi-dimensional information dissemination using COVID-19 data in China," *Comput. Hum. Behav.*, vol. 144, Jul. 2023, Art. no. 107733, doi: 10.1016/j.chb.2023.107733.
[31] P. Tatpornpan, P. M. Prasarnphanich, and C. N. Chiyachantana, "Information quality of investment services with social media," *J. Comput. Inf. Syst.*, vol. 63, no. 2, pp. 310–321, Mar. 2023, doi: 10.1080/08874417.2022.2061639.
[32] S. Zhai, Y. J. Li, and M. Chi, "The impact of government social media information quality on public panic during the infodemic," *Frontiers Psychol.*, vol. 13, May 2022, Art. no. 908213, doi: 10.3389/fpsyg.2022.908213.
[33] Y.-C. Shen, C. T. Lee, L.-Y. Pan, and C.-Y. Lee, "Why people spread rumors on social media: Developing and validating a multi-attribute model of online rumor dissemination," *Online Inf. Rev.*, vol. 45, no. 7, pp. 1227–1246, Oct. 2021, doi: 10.1108/oir-08-2020-0374.
[34] R. Ma, Z. Deng, and M. Wu, "Effects of health information dissemination on user follows and likes during COVID-19 outbreak in China: Data and content analysis," *Int. J. Environ. Res. Public Health*, vol. 17, no. 14, p. 5081, Jul. 2020, doi: 10.3390/ijerph17145081.
[35] H. Z. Brooks and M. A. Porter, "A model for the influence of media on the ideology of content in online social networks," *Phys. Rev. Res.*, vol. 2, no. 2, Apr. 2020, Art. no. 023041, doi: 10.1103/physrevresearch.2.023041.
[36] H. Shen, L. Tu, Y. Guo, and J. Chen, "The influence of cross-platform and spread sources on emotional information spreading in the 2E-SIR two-layer network," *Chaos, Solitons Fractals*, vol. 165, Dec. 2022, Art. no. 112801, doi: 10.1016/j.chaos.2022.112801.
[37] I. Ahmadi, A. Waltenrath, and C. Janze, "Congruency and users' sharing on social media platforms: A novel approach for analyzing content," *J. Advertising*, vol. 52, no. 3, pp. 369–386, May 2023, doi: 10.1080/00913367.2022.2055683.
[38] Z. Amin, N. M. Ali, and R. S. Zinaida, "Tune-attention model: Designing cybernetics intervention for information sharing behavior," in *Proc. 4th Int. Conf. Electron. Electr. Eng. Intell. Syst. (ICE3IS)*, Aug. 2024, pp. 52–56, doi: 10.1109/ICE3IS62977.2024.10775858.
[39] R. Cervero, P. Rosso, and G. Pasi, "Profiling fake news spreaders: Personality and visual information matter," in *Proc. 26th Int. Conf. Appl. Natural Lang. Inf. Syst. (NLDB)*, Germany. Cham, Switzerland: Springer, Jun. 2021, pp. 355–363, doi: 10.1007/978-3-030-80599-9_31.
[40] J. M. Box-Steffensmeier and L. Moses, "Meaningful messaging: Sentiment in elite social media communication with the public on the COVID-19 pandemic," *Sci. Adv.*, vol. 7, no. 29, Jul. 2021, Art. no. eabg2898, doi: 10.1126/sciadv.abg2898.
[41] G. Wang, Y. Wang, K. Liu, and J. Li, "Multidimensional influencing factors of public opinion information dissemination in social media: Evidence from Weibo dataset," *Int. J. Mod. Phys. B*, vol. 33, no. 31, Dec. 2019, Art. no. 1950375, doi: 10.1142/s0217979219503752.
[42] A. Al-Rawi, "Viral news on social media," *Digit. Journalism*, vol. 7, no. 1, pp. 63–79, Jan. 2019, doi: 10.1080/21670811.2017.1387062.
[43] M. J. S. D. A. P. Santos, "Going viral: The influence of emotional content and gender on social transmission," Ph.D. dissertation, Dept. Bus. & Econ., Universidade Católica Portugues, Portugal, 2018.
[44] L. S. Siang and S. Wilson, "Unravelling clickbait news as viral journalism in Malaysia: Its phenomenon and impacts," *SEARCH J. Media Commun. Res.*, vol. 16, no. 1, pp. 33–47, Mar. 2024.
[45] R. Freeman, B. Marder, M. Gorton, and R. Angell, "Would you share that? How the intensity of violent and sexual humor, gender and audience diversity affect sharing intentions for online advertisements," *Inf. Technol. People*, vol. 36, no. 6, pp. 2312–2337, Sep. 2023, doi: 10.1108/itp-09-2021-0679.
[46] Y. Chuai and J. Zhao, "Anger can make fake news viral online," *Frontiers Phys.*, vol. 10, Aug. 2022, Art. no. 970174, doi: 10.3389/fphy.2022.970174.
[47] N. Corbu, A. Bargaoanu, F. Durach, and G. Udrea, "Fake news going viral: The mediating effect of negative emotions," *Media Literacy Acad. Res.*, vol. 4, no. 2, pp. 58–87, Dec. 2021.
[48] A. T. Aston, "Modeling the social reinforcement of misinformation dissemination on social media," *J. Behav. Brain Sci.*, vol. 12, no. 11, pp. 533–547, 2022, doi: 10.4236/jbbs.2022.1211031.
[49] R. E. Petty and J. T. Cacioppo, *Communication and Persuasion*. New York, NY, USA: Springer, 1986.
[50] R. E. Petty and P. Brinol, "The elaboration likelihood model," in *Handbook of Theories of Social Psychology*, P. A. M. Van Lange, A. W. Kruglanski, and E. T. Higgins, Eds., Thousand Oaks, CA, USA: Sage, 2012, pp. 224–245.
[51] D. O. Sears, "Book review: Communication and persuasion: Central and peripheral routes to attitude change by R. E. Petty and J. T. Cacioppo," *Public Opinion Quart.*, vol. 52, pp. 262–265, 1988.
[52] P. Briñol and R. E. Petty, "Elaboration and validation processes: Implications for media attitude change," *Media Psychol.*, vol. 18, no. 3, pp. 267–291, Jul. 2015, doi: 10.1080/15213269.2015.1008103.
[53] S. Teng, K. W. Khong, and W. W. Goh, "Conceptualizing persuasive messages using ELM in social media," *J. Internet Commerce*, vol. 13, no. 1, pp. 65–87, Jan. 2014, doi: 10.1080/15332861.2014.910729.
[54] Y.-T. Chang, H. Yu, and H.-P. Lu, "Persuasive messages, popularity cohesion, and message diffusion in social media marketing," *J. Bus. Res.*, vol. 68, no. 4, pp. 777–782, Apr. 2015, doi: 10.1016/j.jbusres.2014.11.027.
[55] P. J. Kitchen, G. Kerr, D. E. Schultz, R. McColl, and H. Pals, "The elaboration likelihood model: Review, critique and research agenda," *Eur. J. Marketing*, vol. 48, no. 11/12, pp. 2033–2050, Nov. 2014, doi: 10.1108/ejm-12-2011-0776.
[56] G. Kerr, D. E. Schultz, P. J. Kitchen, F. J. Mulhern, and P. Beede, "Does traditional advertising theory apply to the digital world?" *J. Advertising Res.*, vol. 55, no. 4, pp. 390–400, Dec. 2015, doi: 10.2501/jar-2015-001.
[57] M. Srivastava and G. K. Saini, "A bibliometric analysis of the elaboration likelihood model (ELM)," *J. Consum. Marketing*, vol. 39, no. 7, pp. 726–743, Nov. 2022, doi: 10.1108/jcm-12-2021-5049.
[58] M. H. Shahab, E. Ghazali, and M. Mohtar, "The role of elaboration likelihood model in consumer behaviour research and its extension to new technologies: A review and future research agenda," *Int. J. Consum. Stud.*, vol. 45, no. 4, pp. 664–689, Jul. 2021, doi: 10.1111/ijcs.12658.
[59] J. D. Teeny, J. J. Siev, P. Briñol, and R. E. Petty, "A review and conceptual framework for understanding personalized matching effects in persuasion," *J. Consum. Psychol.*, vol. 31, no. 2, pp. 382–414, Apr. 2021, doi: 10.1002/jcpy.1198.
[60] S. Miller, P. Menard, D. Bourrie, and S. Sittig, "Integrating truth bias and elaboration likelihood to understand how political polarisation impacts disinformation engagement on social media," *Inf. Syst. J.*, vol. 34, no. 3, pp. 642–679, May 2024, doi: 10.1111/isj.12418.

[61] Q. Chen, Y. Zhang, R. Evans, and C. Min, "Why do citizens share COVID-19 fact-checks posted by Chinese government social media accounts? The elaboration likelihood model," *Int. J. Environ. Res. Public Health*, vol. 18, no. 19, p. 10058, Sep. 2021, doi: 10.3390/ijerph181910058.

[62] K. K. Kulkarni, A. D. Kalro, and D. Sharma, "The interaction effect of ad appeal and need for cognition on consumers' intentions to share viral advertisements," *J. Consum. Behaviour*, vol. 19, no. 4, pp. 327–338, Jul. 2020, doi: 10.1002/cb.1809.

[63] S. Kumar and S. Khanna, "The relevance of the elaboration likelihood model (ELM) in the consumer buying process in the context of persuasive advertising," *Media Literacy Acad. Res.*, vol. 5, no. 2, pp. 238–258, 2022.

[64] L. Zhou, Z. Zhang, L. Zhao, and P. Yang, "How user personality and information characteristics influence the creative information quality on open innovation platforms: An elaboration likelihood model," *Kybernetes*, vol. 51, no. 7, pp. 2305–2325, May 2022, doi: 10.1108/k-01-2021-0029.

[65] A. R. Ahmad Rizal, S. M. Nordin, W. F. W. Ahmad, M. J. Ahmad Khiri, and S. H. Hussin, "How does social media influence people to get vaccinated? The elaboration likelihood model of a Person's attitude and intention to get COVID-19 vaccines," *Int. J. Environ. Res. Public Health*, vol. 19, no. 4, p. 2378, Feb. 2022, doi: 10.3390/ijerph19042378.

[66] T. Zhou, "Understanding online health community users' information adoption intention: An elaboration likelihood model perspective," *Online Inf. Rev.*, vol. 46, no. 1, pp. 134–146, Jan. 2022, doi: 10.1108/oir-09-2020-0412.

[67] C. Lam, Z. Huang, and L. Shen, "Infographics and the elaboration likelihood model (ELM): Differences between visual and textual health messages," *J. Health Commun.*, vol. 27, no. 10, pp. 737–745, Oct. 2022, doi: 10.1080/10810730.2022.2157909.

[68] N. S. Jayawardena, "The e-learning persuasion through gamification: An elaboration likelihood model perspective," *Young Consumers*, vol. 22, no. 3, pp. 480–502, Jul. 2021, doi: 10.1108/yc-08-2020-1201.

[69] S. Wang, H. Jiang, K. Wang, C. Zhou, J. Bian, J. Yao, and G. Li, "When will government information be attractive? The effect of information features on the diffusion of government microblogs," *Telematics Informat.*, vol. 78, Mar. 2023, Art. no. 101938, doi: 10.1016/j.tele.2023.101938.

[70] S. Chandrasekaran, B. Annamalai, M. Yoshida, S. H. Shabbir, and A. A. Pathak, "Engaging head and heart: Effect of marketer-generated content on social media engagement," *Behav. Inf. Technol.*, pp. 1–21, Apr. 2025, doi: 10.1080/0144929x.2025.2486586.

[71] Q. Liu, F. Su, A. Mu, and X. Wu, "Understanding social media information sharing in individuals with depression: Insights from the elaboration likelihood model and schema activation theory," *Psychol. Res. Behav. Manage.*, vol. Volume 17, pp. 1587–1609, Apr. 2024, doi: 10.2147/prbm.s450934.

[72] Y. Wang, M. Wang, Z. Zhu, and H. Ye, "Uncovering how information quality shapes diverse user engagement on content community platforms: Harnessing deep learning for feature extraction," *J. Theor. Appl. Electron. Commerce Res.*, vol. 19, no. 4, pp. 2673–2693, Oct. 2024, doi: 10.3390/jtaer19040128.

[73] H. Chen, W. Li, T. Lyu, and X. Zheng, "Understanding people's participation in online charities: A dual-process approach of trust and empathic concern," *Ind. Manage. Data Syst.*, vol. 121, no. 7, pp. 1642–1663, Jul. 2021, doi: 10.1108/imds-09-2020-0513.

[74] H. Shim, J. Yeon, and H. Lee, "What makes political rumors contagious: Third-person effect of political rumor dissemination on SNS via dual information processing routes," *Asian Commun. Res.*, vol. 21, no. 3, pp. 475–495, Dec. 2024, doi: 10.20879/acr.2024.21.030.

[75] K. Hur, T. T. Kim, O. M. Karatepe, and G. Lee, "An exploration of the factors influencing social media continuance usage and information sharing intentions among Korean travellers," *Tourism Manage.*, vol. 63, pp. 170–178, Dec. 2017, doi: 10.1016/j.tourman.2017.06.013.

[76] L. Shang, J. Zhou, and M. Zuo, "Understanding older adults' intention to share health information on social media: The role of health belief and information processing," *Internet Res.*, vol. 31, no. 1, pp. 100–122, Jul. 2020, doi: 10.1108/intr-12-2019-0512.

[77] R. V. ShabbirHusain, A. A. Pathak, S. Chandrasekaran, and B. Annamalai, "The power of words: Driving online consumer engagement in fintech," *Int. J. Bank Marketing*, vol. 42, no. 2, pp. 331–355, Mar. 2024, doi: 10.1108/ijbm-11-2022-0519.

[78] Y. Zhao, S. Zhu, Q. Wan, T. Li, C. Zou, H. Wang, and S. Deng, "Understanding how and by whom COVID-19 misinformation is spread on social media: Coding and network analyses," *J. Med. Internet Res.*, vol. 24, no. 6, Jun. 2022, Art. no. e37623, doi: 10.2196/37623.

[79] H. Zheng, D. H.-L. Goh, E. W. J. Lee, C. S. Lee, and Y.-L. Theng, "Understanding the effects of message cues on COVID-19 information sharing on Twitter," *J. Assoc. Inf. Sci. Technol.*, vol. 73, no. 6, pp. 847–862, Jun. 2022, doi: 10.1002/asi.24587.

[80] B. Yang, C. Liu, X. Cheng, and X. Ma, "Understanding Users' group behavioral decisions about sharing articles in social media: An elaboration likelihood model perspective," *Group Decis. Negotiation*, vol. 31, no. 4, pp. 819–842, Aug. 2022, doi: 10.1007/s10726-022-09784-z.

[81] V. Saini, L.-L. Liang, Y.-C. Yang, H. M. Le, and C.-Y. Wu, "The association between dissemination and characteristics of pro-/anti-COVID-19 vaccine messages on Twitter: Application of the elaboration likelihood model," *JMIR Infodemiology*, vol. 2, no. 1, Jun. 2022, Art. no. e37077, doi: 10.2196/37077.

[82] K. Kaushik, A. A. Pathak, and A. Mishra, "Driving pre-match fan engagement through social media: Effects of message characteristics and team performance," *Eur. J. Marketing*, vol. 59, no. 4, pp. 1025–1058, Mar. 2025, doi: 10.1108/ejm-03-2023-0196.

[83] S. Bhagat and D. J. Kim, "Examining users' news sharing behaviour on social media: Role of perception of online civic engagement and dual social influences," *Behav. Inf. Technol.*, vol. 42, no. 8, pp. 1194–1215, Jun. 2023, doi: 10.1080/0144929x.2022.2066019.

[84] S. Sereenonchai and N. Arunrat, "Communication strategies for sustainable urban agriculture in Thailand," *Sustainability*, vol. 16, no. 24, p. 10898, Dec. 2024, doi: 10.3390/su162410898.

[85] T. Baviera and S. Rodriguez, "Shallow engagement in highly engaged pages: The influence of perceived value, content reliability, and homophily on disseminating information on Valencia Bonita Facebook community page," *Int. J. Mark. Commun. New Media*, vol. 11, no. 21, pp. 68–89, Dec. 2023, doi: 10.54663/2182-9306.2023.v11.n21.68-89.

[86] E. Anastasiades, M. Argyrides, and M. Mousoulidou, "Misinformation about COVID-19: Psychological insights," *Encyclopedia*, vol. 1, no. 4, pp. 1200–1214, Nov. 2021, doi: 10.3390/encyclopedia1040091.

[87] H. K. H. Khalifa, "A conceptual review on heuristic systematic model in mass communication studies," *Int. J. Media Mass Commun.*, vol. 4, no. 2, pp. 164–175, Jul. 2022, doi: 10.46988/ijmmc.04.02.2022.007.

[88] M. H. Shahab, E. M. Ghazali, and M. Mohtar, "A systematic literature review and future research agenda for the gratification discrepancies approach," *Contemp. Manage. Res.*, vol. 18, no. 1, pp. 1–33, Mar. 2022, doi: 10.7903/cmr.21583.

[89] J. Cooper, "Cognitive dissonance: Where We've been and where We're going," *Int. Rev. Social Psychol.*, vol. 32, no. 1, May 2019, Art. no. 7, doi: 10.5334/irsp.277.

[90] A. V. Robins, "Dual process theories: Computing cognition in context," *ACM Trans. Comput. Educ.*, vol. 22, no. 4, pp. 1–31, Dec. 2022, doi: 10.1145/3487055.

[91] K. Esfandiar and A. Hadinejad, "A critical review of the theory of planned behaviour in tourism research," *Current Issues Tourism*, pp. 1–15, Jun. 2025, doi: 10.1080/13683500.2025.2522246.

[92] V. Braun and V. Clarke, "Using thematic analysis in psychology," *Qualitative Res. Psychol.*, vol. 3, no. 2, pp. 77–101, Jan. 2006, doi: 10.1191/1478088706qp063oa.

[93] V. Braun and V. Clarke, "One size fits all? What counts as quality practice in (reflexive) thematic analysis?" *Qualitative Res. Psychol.*, vol. 18, no. 3, pp. 328–352, Jul. 2021, doi: 10.1080/14780887.2020.1769238.

[94] V. Braun and V. Clarke, *Thematic Analysis: A Practical Guide*. Newbury Park, CA, USA: Sage, 2022.

[95] V. Braun and V. Clarke, "Reflecting on reflexive thematic analysis," *Qualitative Res. Sport, Exerc. Health*, vol. 11, no. 4, pp. 589–597, 2019, doi: 10.1080/2159676X.2019.1628806.

[96] G. Terry and N. Hayfield, *Essentials of Thematic Analysis*. Washington, DC, USA: American Psychological Assoc., 2021.

[97] J. Fereday and E. Muir-Cochrane, "Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development," *Int. J. Qualitative Methods*, vol. 5, no. 1, pp. 80–92, Mar. 2006, doi: 10.1177/160940690600500107.

[98] H. S. Kim, "Attracting views and going viral: How message features and news-sharing channels affect health news diffusion," *J. Commun.*, vol. 65, no. 3, pp. 512–534, Jun. 2015, doi: 10.1111/jcom.12160.

[99] G. Guest, E. Namey, and M. Chen, "A simple method to assess and report thematic saturation in qualitative research," *PLoS ONE*, vol. 15, no. 5, May 2020, Art. no. e0232076, doi: 10.1371/journal.pone.0232076.

[100] A. Wutich, M. Beresford, and H. R. Bernard, "Sample sizes for 10 types of qualitative data analysis: An integrative review, empirical guidance, and next steps," *Int. J. Qualitative Methods*, vol. 23, Jan. 2024, Art. no. 16094069241296206, doi: 10.1177/16094069241296206.

[101] A. J. M. Zainudin, "X platform dataset from Malaysia news channel (Jan to Oct 2024)," IEEE Dataport, May 2025, doi: 10.21227/fgn0-g759.

[102] D. Byrne, "A worked example of braun and Clarke's approach to reflexive thematic analysis," *Qual. Quantity*, vol. 56, no. 3, pp. 1391–1412, Jun. 2022, doi: 10.1007/s11135-021-01182-y.

[103] V. Braun, V. Clarke, and P. Weate, "Using thematic analysis in sport and exercise research," in *Routledge Handbook of Qualitative Research in Sport and Exercise*, B. Smith and A. C. Sparkes, Eds., Abingdon, U.K.: Routledge, 2016, pp. 191–205.

[104] T. D. Wilson and E. Maceviciute, "Information misbehaviour: Modelling the motivations for the creation, acceptance and dissemination of misinformation," *J. Documentation*, vol. 78, no. 7, pp. 485–505, Dec. 2022, doi: 10.1108/jd-05-2022-0116.

[105] Y. Sun and J. Xie, "Do heuristic cues affect misinformation sharing? Evidence from a meta-analysis," *Journalism Mass Commun. Quart.*, Oct. 2024, doi: 10.1177/10776990241284597.

[106] J. Yan, Y. You, Y. Wang, and D. Sheng, "Understanding the complexity of business information dissemination in social media: A meta-analysis of empirical evidence from China," *Complexity*, vol. 2021, no. 1, Jan. 2021, Art. no. 7647718, doi: 10.1155/2021/7647718.

[107] K. A. Qureshi, R. A. S. Malick, M. Sabih, and H. Cherifi, "Complex network and source inspired COVID-19 fake news classification on Twitter," *IEEE Access*, vol. 9, pp. 139636–139656, 2021, doi: 10.1109/ACCESS.2021.3119404.

[108] S. Segev and J. Fernandes, "The anatomy of viral advertising: A content analysis of viral advertising from the elaboration likelihood model perspective," *J. Promotion Manage.*, vol. 29, no. 1, pp. 125–154, Jan. 2023, doi: 10.1080/10496491.2022.2108189.

[109] J. Zainudin, N. M. Ali, A. F. Smeaton, and M. T. Ijab, "Intervention strategies for misinformation sharing on social media: A bibliometric analysis," *IEEE Access*, vol. 12, pp. 140359–140379, 2024, doi: 10.1109/ACCESS.2024.3469248.

JUANITA ZAINUDIN is currently pursuing the Ph.D. degree with the Institute of Visual Informatics (IVI), Universiti Kebangsaan Malaysia. Alongside her studies, she also a Lecturer with the Faculty of Computing and Multimedia, Universiti Poly-Tech Malaysia, where she imparts her knowledge to the next generation of scholars. Her research interests include the field of human–computer interaction (HCI), information behavior, and misinformation sharing.

NAZLENA MOHAMAD ALI received the Ph.D. degree in human–computer interaction from Dublin City University, Ireland. She is currently a Senior Research Fellow and an Associate Professor with the Institute of Visual Informatics (IVI), Universiti Kebangsaan Malaysia. Her research interests include user interface and user experience (UI/UX), persuasive design, and behavior analytic.

ALAN F. SMEATON (Fellow, IEEE) is currently an Emeritus Professor of computing and the Former Director of the Insight–Centre for Data Analytics, Dublin City University. His research interests include human memory, why we forget some things and not others, and how we can use technology like search systems, to compensate for when we do forget. He was the winner of the Royal Irish Academy Gold Medal for Engineering Sciences, in 2015. He was the Chair of ACM SIGMM.

MOHAMAD TAHA IJAB received the Ph.D. degree in business IT from RMIT University, Australia. He is currently a Research Fellow with the Institute of Visual Informatics (IVI), Universiti Kebangsaan Malaysia. He is interested and researching in the fields of social and environmental informatics, business process management, and organizational management in informatics.

Scopus Preview

Source details

IEEE Access

Open Access

Years currently covered by Scopus: from 2013 to 2025

Publisher: IEEE

E-ISSN: 2169-3536

Subject area: Engineering: General Engineering | Computer Science: General Computer Science | Materials Science: General Materials Science

Source type: Journal

View all documents > | Set document alert | Save to source list

CiteScore 2024
9.0

SJR 2024
0.849

SNIP 2024
1.504

CiteScore | CiteScore rank & trend | Scopus content coverage

CiteScore 2024

9.0 = 402,859 Citations 2021 - 2024 / 44,988 Documents 2021 - 2024

Calculated on 05 May, 2025

CiteScoreTracker 2025

8.4 = 375,993 Citations to date / 45,017 Documents to date

Last updated on 05 December, 2025 • Updated monthly

CiteScore rank 2024

Category	Rank	Percentile
Engineering — General Engineering	#32/344	90th
Computer Science — General Computer Science	#33/239	86th

View CiteScore methodology > | CiteScore FAQ > | Add CiteScore to your site