

The Power of Words: Driving Online Consumer Engagement in Fintech

Abstract

Purpose: This study aims to explore the role of the linguistic style used in the brand-posted social media content on consumer engagement in the Fintech domain.

Design/methodology/approach: 3286 tweets (registering nearly 1.35 million impressions) published by 10 leading Fintech unicorns in India were extracted using the Twitter API. The Linguistic Inquiry and Word Count (LIWC) dictionary was used to analyse the linguistic characteristics of the shared tweets. Negative Binomial Regression (NBR) was used for testing the hypotheses.

Findings: Our study finds that using drive words and cognitive language increases consumer engagement with Fintech messages via the central route of information processing. Further, affective words and conversational language drive consumer engagement through the peripheral route of information processing.

Practical implications: The study provides guidance to social media marketers of Fintech brands regarding what content strategies best enhance consumer engagement. The linguistic style to improve online consumer engagement is detailed.

Research implications: The study extends the literature on brand engagement by unveiling the effect of linguistic features used to design social media messages.

Originality/value: Our findings contribute to the growing stream of Fintech literature by exploring the role of linguistic style on consumer engagement in social media communication. Our findings indicate the relevance of the dual processing mechanism of ELM as an explanatory theory for evaluating consumer engagement with messages posted by Fintech brands.

Keywords: consumer behaviour; elaboration likelihood model; Fintech; linguistic functions; online consumer engagement; social media branding; Twitter

1. Introduction

The need to grow market share and rapidly increase consumer base becomes crucial for brands in nascent and rapidly evolving industries such as the Fintech industry in India (Gandhi, 2022). The Fintech industry in India has grown rapidly due to a mix of factors, including regulatory support, improved infrastructure, growth of the economy, and favourable population demographics (Pillai *et al.*, 2019; Shah, 2022). By 2030, the sector is forecasted to achieve an annual throughput of one trillion dollars and about \$200 billion in revenue (Shah, 2022). India is among the fastest-growing Fintech markets globally, with a compound annual growth rate of about 24.5 per cent and a market size of \$50 billion in 2021 (Invest India, 2022). However, the proliferation of start-up ventures and subsidiaries of established financial sector brands in the industry has led to intense competition among Fintech brands to attract consumers and gain market share (Hussain, 2023).

Social influence plays a significant role in Fintech adoption (Singh *et al.*, 2020). It refers to the extent of influence of others on one's adoption of technology. The role of social influence becomes more critical for adopting technological innovations, like Fintech, where people give greater importance to the opinions/views of others in the absence of their own experience while engaging with a brand. In this regard, the social media platforms, such as Instagram, Facebook, and Twitter, play a pivotal role in bridging the brand with the consumers through effective engagement (Annamalai *et al.*, 2021). Social media platforms have grown in terms of user base and increased consumer engagement behaviour manifested through browsing, participating, and transacting (Oh *et al.*, 2017). The platforms act as outlets for brand-generated and user-generated content that the consumers engage with (Khan and Ahmad, 2021).

A consumer's willingness to be involved with the brand is defined as consumer engagement and refers to the consumer's cognitive, emotional, and behavioural activities related to the brand (Hollebeek, 2011; Glavee-Geo *et al.*, 2019). By engaging with consumers, brands can build

1 and maintain strong relationships with them, resulting in the provision of benefits such as
2 higher emotional value and perceived trust (Chakraborty *et al.*, 2022), value creation
3 (Laksamana *et al.*, 2022), and increasing brand awareness (Barbosa *et al.*, 2022). Brands are
4 increasingly using social media platforms to promote engagement with consumers. Extant
5 online literature bifurcates social media content as marketer-generated and user-generated
6 content to study the actions of brands and consumers (Saura *et al.*, 2021; Saura *et al.*, 2022).
7 As engagement predominantly happens as a response to the social media post by the brand,
8 brands need to formulate an effective content strategy to drive online consumer engagement
9 (OCE; Chandrasekaran *et al.*, 2019). The content strategy primarily covers "what messages to
10 post" and "how to design the messages" to maximise OCE on social media (Nguyen *et al.*,
11 2015). Therefore, brands must be cognizant that both the message content and the linguistic
12 style used in their social media shape 'consumers' perception, memory, attitude, and behaviour'
13 (Deng *et al.*, 2021b).

14 Extant literature on social media content strategy is dominated by focusing on what is
15 communicated through the text message than how the message is presented (Lee and Kahle,
16 2016). For instance, past researchers have explored the effects of content type, media type, the
17 number of hashtags used, and time and frequency of posting on OCE (Ma *et al.*, 2022,
18 Annamalai *et al.*, 2021, Zhang and Su, 2022). However, knowing how to design the message
19 using suitable language is equally important to enhance OCE (Deng *et al.*, 2021b). Studies on
20 the effect of linguistic styles on social media posts are still nascent (Deng *et al.*, 2021b;
21 Carnevale *et al.*, 2017). Research has examined linguistic roles in persuasion by studying the
22 aspects of certainty (Li *et al.*, 2021; Pezzuti *et al.*, 2021) and proximity (Zhu, 2022; Labrecque
23 *et al.*, 2020), thereby emphasising how variations in words can shape consumers' processing
24 and evaluation of messages. The linguistic styles that characterise the social and psychological
25 processes are also likely to shape the impact of information (Pennebaker *et al.*, 2015). Such

words can also induce relational perceptions in consumers (Ludwig *et al.*, 2013). This study provides a nuanced understanding of the effect of subtle distinctions in linguistic choices on OCE. Since, expectations of consumers in emergent categories (like Fintech) may not be entirely well defined. To compensate for this lack of expectation, consumers take additional support from cues like linguistic styles to form viewpoints (Parhankangas and Renko, 2017). Hence, it is essential to study the influence of linguistic styles on OCE in this context.

Research on social media content strategy has explored the influence of brand content on OCE and observed it to be context-specific depending on the sectoral characteristics (Annamalai *et al.*, 2021; Shahbaznezhad *et al.*, 2021; Tafesse and Wien, 2018). Extant literature has studied OCE in internet and mobile banking (Moliner-Tena *et al.*, 2019; Ferm and Thaichon, 2021; Glavee-Geo *et al.*, 2019). However, OCE in the Fintech context has gained limited attention, and further research is needed to advance the understanding of branding financial institutions through effective social media engagement (Glavee-Geo *et al.*, 2019; Savitha and Hawaldar, 2022). For digital-first sectors like Fintech, there is a high reliance on social media platforms to connect with customers and provide them with financial services (Oh *et al.*, 2023). Hence, examining individuals' reactions, expectations and evaluations of social media messages relating to Fintech brands (Dootson *et al.*, 2016) is essential. By studying OCE, Fintech companies can better understand drivers of customer behaviour, their preferences, and their needs. Understanding the linguistic features of social media messages can help firms identify how customers interact with their brand and what types of messages resonate with them (Deng *et al.*, 2021a). This information can be used for tailoring social media content to improve customer engagement and build a stronger brand relationship. The tone and language style used in social media messages significantly impacts OCE. Thus, to garner greater OCE, it is essential to understand whether a Fintech brand should use a friendly, conversational tone (avoiding complex or technical jargon) or be more objective in its messaging. Given the emergent nature

of the Fintech industry, the rapid growth in business in terms of value and volume of Fintech brands (Savitha and Hawaldar, 2022), and their need to target the young and digitally savvy generation consumers, a better understanding of how brands state their message (i.e. the linguistic style), is needed.

In response to this need, the present study addresses the following research question: *What is the impact of linguistic features of a social media message from Fintech brands on OCE?* In answering this question, we aim to achieve the following objectives:

- To contribute to the growing stream of Fintech engagement literature
- To explore the role of linguistic style on OCE in social media communication
- To establish the relevance of the dual processing mechanism for evaluating OCE in the Fintech domain

The study is grounded in the widely used persuasion theory of elaboration likelihood model (ELM) that posits persuasion to act via the central or the peripheral routes (Cacioppo and Petty, 1984). The study focuses on OCE with tweets shared by India's ten leading Fintech unicorns (by value). Over 3,000 tweets by various Fintech brands and nearly 1.35 million impressions over a year are investigated. LIWC dictionary (Pennebaker *et al.*, 2015) is used to classify the linguistic characteristics of the tweets as having drive words, cognitive words, affective words and conversational words. In line with the extant literature, the OCE is estimated using the number of likes, replies and retweets (Deng *et al.*, 2021a; Chandrasekaran *et al.*, 2022). The hypothesised relationships among the variables of interest are tested using multilevel negative binomial regression.

The rest of this paper is structured as follows. In Section 2, we review relevant literature to develop study hypotheses. A discussion on methodology and data analysis in Section 3 follows this. We then share the results and provide a detailed discussion of the results in Section 4 and

Section 5. Finally, we conclude with theoretical and practical implications and the study limitations in Section 6.

2. Theoretical background and Hypotheses building

2.1 Online consumer engagement

Consumer engagement is "the level of a customer's motivational, brand-related and context-dependent state of mind, characterised by specific levels of cognitive, affective and behavioural activity in brands" (Hollebeek, 2011, pp. 785). The cognitive dimension refers to the extent a brand can serve a consumer's self-interest, thereby triggering the cognitive involvement of the consumer in the consumer-brand interaction. Such involvement requires serious attention (Dessart *et al.*, 2016) and immersion (Hollebeek, 2011) by the consumers in the interactions, leading to cognitive engagement. On the other hand, the affective dimension refers to the ability of a brand to build an emotional bonding with the consumer. Such bonding aids consumers in identifying with the brand (Barbosa *et al.*, 2022) and invokes a hedonic attachment to the brand. This intrinsic excitement created by the brand in an interaction reflects affective engagement. Lastly, the behavioural dimension that encapsulates the outward manifestation of consumer involvement is largely emulated on online platform in the recent times (Perez-Vega *et al.*, 2021).

Consumers engage with a brand through one of the most omnipresent online social media channels (Barbosa *et al.*, 2022). On social media, the liking response to a post is considered an affective OCE, replying/commenting response is considered a cognitive OCE, and retweeting/sharing response is a combination thereof (Swani and Labrecque, 2020; Kim and Yang, 2017). Consumers exert more cognitive effort for replies than likes, as the latter is ephemeral and requires only a single click. Liking represents the lowest social media engagement level and is driven by affective brand relationships (Swani and Labrecque, 2020). On the other hand, replies/comments require clicking the comment button, reading original

posts and subsequent comments, typing an appropriate response and then posting the response, making the commenting behaviour more reflective and requiring more significant cognitive processing (Swani and Labrecque, 2020). Retweets also necessitate high commitment as the shared content constitutes a part of the consumer's self-presentation (Swani and Labrecque, 2020; Kim and Yang, 2017).

Understanding OCE is particularly important in emerging area like Fintech since OCE can result in more long-term interactions and foster consumer loyalty and advocacy through electronic word-of-mouth (Glavee-Geo *et al.*, 2019). Since, Fintech firms deal with sensitive financial data and transactions, building online engagement can go a long way for them in building trust and strong relationships with consumers (Laksamana *et al.*, 2022). The Fintech brands create value through active consumer engagement, education and information sharing on social media (Breidbach and Ranjan, 2017). The OCE, achieved through real-time social media communication as well as promotional activities, acts as a key enabler to enhance the brand's service reputation (Oh *et al.*, 2023; Sahai *et al.*, 2018).

2.2 Elaboration likelihood model

ELM is a dual process theory that describes how individuals process information. ELM provides a framework for understanding stimuli processing and its impact on persuasive communication (Cacioppo and Petty, 1984). The model suggests that attitude formation happens along the elaboration continuum ranging from "low" to "high". Based on the elaboration level of the message, there are two routes taken for message processing while forming attitude: the central and peripheral routes. When the message falls at the lower end of the elaboration continuum, the peripheral route is adopted for message formation, and messages at the higher end of the elaboration continuum use the central route (Kruglanski *et al.*, 2012). While the central route involves detailed high-involvement consideration of arguments in the message, attitude formation via the peripheral route involves minimal

processing in which simple heuristics or shortcuts are used for information processing (Cacioppo and Petty, 1984). Past studies suggest that central cues involve issue-relevant information that provides evidence/arguments directly related to the product/service. In contrast, peripheral cues entail affective components like message tone and source status (Lee *et al.*, 2019).

ELM has been a widely used theory in social media communication research. Research has applied ELM to study social media post characteristics such as content type, media type, time/day and frequency of posting (Chandrasekaran *et al.*, 2022; Khan and Ahmad, 2021). Recently, the persuasive role of linguistic styles has been investigated with the help of ELM. Studies have examined the role of linguistics in brand communication (Deng *et al.*, 2021a), government communication (Feng *et al.*, 2021), social media influencer communication (Munaro *et al.*, 2021) and political communication (Hagemann and Abramova, 2023). These studies suggest that the ELM can explain what characteristic of social media content enables which type of information processing route. Following these previous studies, this study proposes to examine the influence of linguistic styles on OCE in the Fintech context.

2.3 Linguistic style

Language is a prevalent way for consumers to render their internal thoughts and emotions into an understandable form for others. On social media, the linguistic features are of increased importance as they represent the endogenous characteristics of the brand-shared post (Ludwig *et al.*, 2013). Recent research shows that the psycho-linguistic style of social media posts is an important predictor of OCE (Lee *et al.*, 2018). Deng *et al.*, (2021b) have studied the impact of brand-post linguistic styles, such as emotionality, complexity and informality, on OCE behaviours. Table I summarises prior studies on the role of linguistic styles. The studies reviewed in the table highlight the need to explore the brand posts' related linguistic features

that influence OCE behaviours. In particular, language plays a significant role in the high-stakes Fintech environment requiring increased trust and persuasion (Larrimore *et al.*, 2011). Therefore, the current research explores the persuasive impact of linguistic features of Fintech brand posts on OCE.

Table I: Relevant previous studies on the role of linguistic styles

Author(s)	Description
Ludwig <i>et al.</i> ,(2013)	Analysed linguistic styles of customer reviews to extract insights on e-commerce sites' conversion rate
Parhankangas and Renko (2017)	Compared the linguistic style of crowdfunding pitches made by social entrepreneurs and commercial entrepreneurs on the success of social crowdfunding campaigns
Lee <i>et al.</i> ,(2019)	Analysed the narrative pitch on civic crowdfunding projects on funding outcomes
Deng <i>et al.</i> ,(2021a)	Measured the linguistic characteristics of brand posts and studied their influence on B2B brand engagement on social media
Deng <i>et al.</i> ,(2021b)	Explored the influence of Facebook brand posts linguistics on consumer engagement
Hlee <i>et al.</i> ,(2021)	Explored linguistic factors that contribute to the helpfulness of reviews on online tourism destinations
Lin and Boh (2021)	Analysed the effect of linguistic style on information reliance by crowd funders on the project funding decision

How a message is delivered is of utmost importance in entrepreneurial firms since narratives play a significant role in conveying value and setting expectations (Chen *et al.*, 2009; Martens *et al.*, 2007). Specifically, language elements and style influence the audience in the rapidly growing Fintech domain (Koh *et al.*, 2020). Linguistic styles have been noted to influence the sourcing (Lee *et al.*, 2019) and the deployment of funds (Herzenstein *et al.*, 2011). The linguistic style is characterised by the functional and emotional words embedded in the message content that drives consumers' social and psychological processes (Pennebaker *et al.*, 2015). The psychological processes of messages are primarily reflected through drive words, cognitive words, affective words, conversational words and social processes (Pennebaker *et al.*, 2015). While similar to social processes, conversational words have been endorsed over social processes since they capture informal language (e.g., hi, lol, thanks, ok; Verheijen and

van Hout, 2022). Such words account for uncertainty and humanise language. Evaluating informal language is critical in the case of Fintech since messages are targeted towards the younger, tech-savvy audience (Gulamhuseinwala *et al.*, 2015) that is more likely to use informal language in their communication (De Cicco *et al.*, 2020). Also, Fintech messages can be complex; hence, accounting for uncertainty is essential. Finally, Fintech messages can be technical and jargon-heavy; hence, it is essential to understand the humanising implications of language. Hence, analysing language characteristics from the lens of drive, cognitive, affective and conversational words would be ideal.

The current study envisages the role of central and peripheral routes in processing the Fintech brand messages. We leverage ELM to study the impact of greater informational provisioning along the central route via using a more cognitive language and drive words and along the peripheral route via usage of affective and conversational language. The cognitive route of processing involves information processing by an individual that is more deliberate, conscious and effortful (Deng *et al.*, 2021a). It is associated with situations wherein individuals are motivated to carefully consider the information presented as they evaluate a communication/product or make a decision. "Drive words" are typically designed to elicit users' emotions like fear, excitement or desire (Koh *et al.*, 2021). As a result, individuals are likely to engage in more deliberate and effortful thinking, invoking the central processing route.

Similarly, "cognition words" engage an individual's cognitive processes like attention, perception and memory (Hlee *et al.*, 2021; Pennebaker *et al.*, 2015). These words typically help in promoting understanding and recall of the message. In the case of Fintech, these words may include technical numbers, statistics and even terms like "Fintech API". These words are likely to invoke a careful deliberation and hence follow the cognitive processing route. Thus, "drive words" and "cognitive words" crucially represent the cognitive processing route since they are typically associated with more effortful deliberate thinking.

The peripheral processing route involves information processing by an individual that is less effortful, less conscious and more automatic (Deng *et al.*, 2021a; Lin and Boh, 2021). It is usually associated with situations wherein individuals may not have strong internal motivation to consider the information carefully. "Affective words" are typically designed to elicit emotional responses like happiness, sadness or anger from users (Pennebaker *et al.*, 2015). These may include emotional adjectives or other figurative language tools to influence an individual's mood or feelings. When individuals come across these terms, they are likely to engage less in a more automatic, less conscious processing of information and develop emotional responses following the peripheral processing route (Ludwig, 2013). Similarly, "conversational words" create a friendlier, more approachable tone (Pennebaker *et al.*, 2015). When readers come across these messages, they are likely to be more engaged with the tone of the message and the personal relationship that is invoked. In this case, the information processing is likely to follow a less conscious and more automatic peripheral route of processing.

The conceptual model is shown in Figure 1. Next, we provide our detailed argumentation around the influence of drive words, cognitive language, affective language and conversational language.

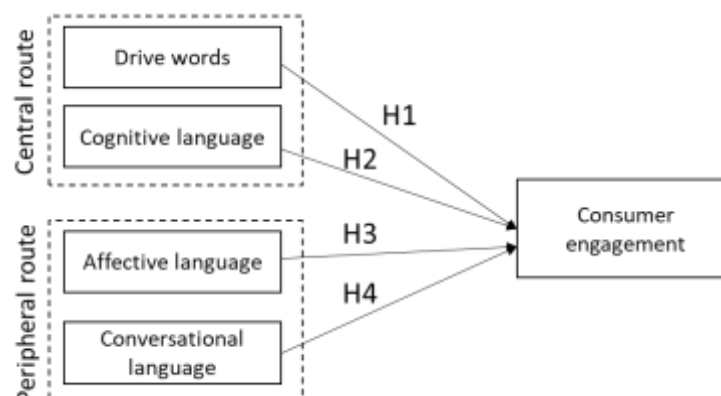


Figure 1: Conceptual Model

2.4 Drive words

Drive words are associated with affiliation, achievement, reward, power and risk (Malik and Hussain, 2018). Examples of drive words include friend, doubt, and danger. They capture the needs and motives in a message (Pennebaker *et al.*, 2007). Drive words reflect a need for self-accomplishment and self-empowerment (Yan and Yang, 2021). The achievement words refer to success, failure and accomplishments; power words signify status and social ranks, while reward words include textual cues related to compensations, motivations and aspirations.

Consumer groups that are highly self-driven and have motives of self-achievement are likely to engage more with drive words (Yan and Yang, 2021). Consumers engaging with a Fintech platform are likely to have a greater propensity to process messages that deal with elements related to risk, reward, achievement and recognition– all of which fall under the gamut of drive words. As a result, drive cues may lead to greater consumer involvement with the Fintech platform. Voss *et al.*, (2003) suggested a two-dimensional view of an individual's involvement and subsequent informational processing via the central route of persuasion. They argued that information that impacts an individual's feelings and achievements, resulting in certain emotional states (Zaichkowsky, 1994), results in affective involvement and a subsequent positive brand attitude via the cognitive processing route. Extending this, we argue that since drive words generate feelings of affiliation ("we", "us"), achievement ("best", "working"), and reward ("win", "benefit"), they are likely to influence consumers' affective engagement via the central route.

In line with our above arguments, past studies have also noted the role of drive words in processing information through the central processing route (Malik and Hussain, 2018). In a comparison across seven countries, Koh *et al.*, (2021) found that drive words had a significant

positive association with consumers' likelihood to engage across all geographies. Similarly, Berman *et al.*,(2019) noted that social media messages that carried drive words were likely to be shared and posted by bloggers with a large follower base. Since processing the emotive drive words is likely to exert increased affective effort, it will likely invoke the affective measure of engagement. In light of these arguments and findings, we hypothesise that:

H1: The use of drive words positively influences affective OCE.

2.5 Cognitive language

A message describing beliefs and rational aspects of a product/service is classified as a cognitive message (Hlee *et al.*, 2021). Cognitive language is used to signal causality, insights, the transmission of facts and the provision of explanation through the usage of words like "know" and "because" (Makenna *et al.*, 2019; Brownlow, 2020). Cognitive language is also reflected in cases of discrepancies, tentativeness ("should", "maybe"), differentiation ("but") and certainty ("always").

The objective language contained with cognitive cues includes factual, attribute-centric information that may help in search-type information (Hlee *et al.*, 2021). These objective features of language content have been established to strongly impact consumer judgement (Jeong and Koo, 2015), likely through the central processing route, and subsequently impacting OCE. This influence on the consumer is explained by objectivity bias (Hlee *et al.*, 2021). The objective information contains more factual information related to search-type information (Jeong and Koo, 2015). Processing this cognitive information stimulates an intellectual mechanism that drives thinking, reasoning or remembering, thus invoking the central processing route.

This element of objectivity in the cognitive language will likely play a more decisive role in Fintech messages, given the financial risk-reward implications that may be involved with those

1 messages. In messages involving Fintech, where consumers may have a greater feeling of
2 uncertainty and risk, consumers are likely to seek more factual, rational messages that carry
3 cognitive cues (Hlee *et al.*, 2021). Voss *et al.*,(2003) argued that when rational thinking based
4 on logic is undertaken, it invokes greater cognitive involvement and, subsequently positive
5 brand attitude from the consumer via the central processing route. Since processing cognition
6 words is likely to exert increased cognitive effort, it is likely to invoke the cognitive measure
7 of engagement. In line with the above arguments, we hypothesise that:

8 *H2: The use of cognitive language influences cognitive OCE.*

9 *2.6 Affective language*

10 Linguistic cues, particularly affective language cues, have been noted to drive consumers'
11 decision-making (Lee *et al.*, 2019). Affective words convey emotions, like happiness, anger
12 and sadness (Ludwig *et al.*, 2013) and reveal the intention of the message (Das *et al.*, 2005).
13 Only reading a text with affective language might be sufficient to influence thoughts and
14 behaviours (Lench *et al.*, 2011). This is because affective cues automatically elicit emotional
15 responses that require lower processing resources, emerge rapidly and guide actions (Ludwig
16 *et al.*, 2013). The influence of affective content on OCE may be pronounced for consumers
17 who are not mainly motivated to engage in cognitive processing and/or those with limited
18 processing capabilities (Ludwig *et al.*, 2013). Affective language is reflected in form of
19 positive/negative tone ("good", "love", "hate", "wrong"), positive and negative emotions
20 ("happy", "tired", "worry", "angry", "disappointed") and even swear words ("damn").

21 Affective cues in message text are likely to influence respondents' attitudes, particularly in the
22 online environment, with the heuristic nature of online information processing driving
23 consumer actions (Das *et al.*, 2005). The influence of affective content on consumers gets
24 accentuated when consumers lack domain expertise (Cohen *et al.*, 2018; Greifender *et al.*,

2011). This was reflected in the early days of online purchases (Jones *et al.*, 2004), where affective textual content provided diagnostic signals that drove consumer engagement (Cohen *et al.*, 2018). We believe that Fintech is at its early stage, and thus affective content may significantly influence OCE. Lee *et al.*, (2019) observed that in the specific Fintech domain of crowdsourcing, the affective component of messages (how one communicates) that sought funding impacted consumer persuasion and engagement. They further noted that affective cues in messages followed the peripheral route of persuasion. These affective stimuli help consumer form perceptions of credibility, legitimacy and attractiveness of the message sender (Lee *et al.*, 2019), thereby impacting engagement in the Fintech domain.

Hence, we hypothesise that:

H3: The use of affective language positively influences OCE.

2.7 Conversational language

Conversational language has been associated with improving consumers' evaluation of a message through increased interactivity (Deng *et al.*, 2021a; Jakic *et al.*, 2017). Conversational language takes the form of netspeak ("lol", "haha"), fillers ("wow", "youknow"), nonfluencies ("oh", "uh") and assent ("yeah", "okay"). Using Communication Adaption Theory and linguistic style matching, Jakic *et al.*, (2017) suggested that conversational language signifies a higher relationship investment resulting in a higher perceived benevolence and hence greater OCE. Along these lines, Stone and Can (2020) found in their study on Twitter that tweets that contained warm and conversational language were more likely to get OCE by inspiring group affiliation and a common purpose. We argue that these conversational signals act as strong peripheral cues, particularly in social media-based interactions, where interactions are primarily focused on verbal cues and language styles (Kurtzberg *et al.*, 2009). These peripheral cues become increasingly important in building trust under risk conditions (Shneor *et al.*,

2021). The role of trust in online financial exchanges has grown dramatically over the last few years (Shneor *et al.*, 2021). Hence, the role of these peripheral cues generated by conversational language will likely impact OCE positively. We, hence, hypothesise that:

H4: The use of conversational language positively influences OCE.

3. Methodology

3.1 Data

With over 211 million daily active users, Twitter has become an essential platform for consumer engagement in social media (Statista, 2022). Twitter has been the most extensively used platform by financial brands to promote their products and services in India (Singh *et al.*, 2019). Further, conversations related to finance and investing have been the top trending topic in the year 2020-2021 (Twitter trends, 2022). Hence Twitter platform was considered for the study. The COVID-19 restrictions were unlocked across India by June 15, 2021. This study considered an extended one-year after that, i.e., from June 16, 2021, to June 15, 2022. The study considered the 10 leading Fintech unicorns by value in India with an official Twitter handle (Statista, 2022). The unicorn start-ups considered for the study are detailed in Table II. The tweets were collected using Twitter Developers account¹. The account grants security token for the Twitter API, which can be implemented using various programming languages such, as Python or R. The token created for such account grants access to full archive of historical tweets and tweets related to different types of queries. For example, it is possible to retrieve the tweets of a specific handle (e.g., Paytm) or all the tweets within a specific time period containing specific words or hashtags (e.g., #PaytmCricketLeague). The token also allows a download of 10 million tweets per month at a frequency of 500 tweets per second. The tweets retrieved include information on functional (e.g., hashtags, mentions and URLs)

¹ <https://developer.twitter.com/>

and contingent (e.g., reply, retweet or original) features of the tweet, number of likes, replies and retweets, and account related information. A total of 3286 tweets published in English from the verified Twitter handles (identified by a blue tick mark) were considered for the study. The unit of analysis is the tweet shared by the official Fintech companies.

3.2 Variable operationalisation

3.2.1 Dependent variable

In line with the previous research (Chandrasekaran *et al.*, 2022; Hinson *et al.*, 2019), OCE was measured using the contribution activities: the number of likes, replies, and retweets recorded against a tweet. The number of likes is considered an affective measure of OCE, and the number of replies is considered the cognitive measure of OCE. The number of retweets is considered an affective and a cognitive measure of OCE (Kim and Yang, 2017).

Table II: Fintech unicorn start-up handles on Twitter

Company name	Verified handle name	Follower count	Total tweet count
Bharat Pe	bharatpeindia	16833	43
CoinDCX	CoinDCX	228010	812
Coinswitch	CoinSwitchKuber	101267	893
CRED	CRED_club	50054	36
Groww	_groww	66021	139
Paytm	Paytm	1317576	482
PhonePe	PhonePe	171064	226
Pine Labs	PineLabs	6678	145
PolicyBazaar	policybazaar	21628	141
RazorPay	Razorpay	21345	369

3.2.2 Independent variables

LIWC dictionary (Pennebaker *et al.*, 2015) was used to analyse the linguistic characteristics of the shared tweets. LIWC is a quantitative text analysis tool that ascertains what is being said (content) and how it is being said (style). The dictionary consists of words validated to measure the manifestation of psychological constructs in the textual content. It works on the assumption

that people often convey psychological information along with the text's literal meaning (Scholand *et al.*, 2010). The commercial and academic versions are available online (www.liwc.app). Many social media content analysis studies have adopted this tool to analyse message-related linguistic characteristics (Lee *et al.*, 2018; Yoon *et al.*, 2018; Deng *et al.*, 2021a; Deng *et al.*, 2021b; Dhaoui and Webster, 2021). The dictionary consists of pre-defined word categories reflecting psychological states such as drives, affect, cognition, and conversation, which are the measures of the independent variables. Each variable is measured as the percentage of words in a tweet message that measures a particular psychological state. In LIWC, the psychological process of drive comprises 1477 words denoting affiliation, achievement, and power (e.g., we, our, work, us). The psychological process of cognition in LIWC includes 1403 words that largely detail the cognitive processes and memory reflecting the different ways of thinking (e.g., think, feel, why, remember). The psychological process of affect primarily includes 2999 words detailing tonality that reflect sentiments and emotions (e.g., good, well, love, hope). The conversational language consists of 500 entries, including informal words such as assent and non-fluencies (e.g., okay, yes, oh, yeah). The strength of a linguistic element is expressed as the percentage of total words in the tweet.

Further, the LIWC results were validated using the procedure of Huang and Yeo (2018). Thirty tweets from each of the four focal categories were randomly selected and manually coded. The LIWC's definition and explanation of the four categories were used to train the coder. The coder rated the tweets on a five-point Likert scale (1 – very low to 5 –very high). The coded results were correlated with the LIWC score of the tweets to evaluate their validity. Correlation results reveal positive and significant relation between the coder's score and LIWC score in all four categories ($r_{\text{drives}}=0.73$, $p<0.05$; $r_{\text{cognition}}=0.73$, $p<0.05$; $r_{\text{affect}}=0.74$, $p<0.05$; $r_{\text{conversational}}=0.77$, $p<0.05$), thus indicating good validity of LIWC scores (Huang and Yeo, 2018). Table III shows the LIWC output for a sample of tweets in each category.

Table III: Examples of LIWC output

Tweets	LIWC category and score
The initiative to synergise clean air efforts is here! Together, we can #BeatAirPollution	Drive words 30.77
Earn equally. Manage equally. #WomensDay	Cognitive language 60
Wishing you and your loved ones a very happy Holi #HappyHoli https://t.co/YLW6czeu6v	Affective language 22.22
Johnny Yes papa Did your own research? Yes papa Open your portfolio Hahaha	Conversational language 21.43

3.2.3 Control variables

Given that content characteristics influence OCE, tweet length (measured as the number of words in a tweet), presence of hashtag, day of posting (measured as weekday or weekend), and the tweet's media type were used as control variables to adjust for possible confounds (Pezzuti *et al.*, 2021; Soboleva *et al.*, 2017). All data pre-processing and analysis were performed using the open-source R programming language.

3.3 Analysis method

Studies have used linear regression by log transforming the dependent variables that are count variables by nature (Table IV). Count variables are inherently limited to non-negative values, and fitting conventional Gaussian models by log transforming or 'log1plus' transforming can lead to a higher likelihood of false-positive inferences (Cohn *et al.*, 2022).

Table IV: Methods used in relevant previous studies on online platforms

Author(s)	Research design	Data set	Analysis
Lee <i>et al.</i> , (2019)	Quantitative	Campaign information on crowdfunding platform	Logistic regression
Stone and Can (2020)	Quantitative	Twitter data	Linear regression
Deng <i>et al.</i> , (2021a)	Quantitative	Twitter data	Linear regression
Deng <i>et al.</i> , (2021b)	Quantitative	Facebook data	Multilevel regression

Shneor <i>et al.</i> , (2021)	Quantitative	Campaign information on crowdfunding platform	Linear regression, Logistic regression
Current study	Quantitative	Twitter data	Multilevel negative binomial regression

To test the hypotheses, we used Negative Binomial Regression (NBR), which is commonly employed for modelling over-dispersed count data. In this study, the dependent variables were count variables: the number of likes, replies, and retweets, exhibiting over-dispersion (Table V).

Table V: Descriptive statistics of engagement measures

Variable	Description	Mean	Variance	Min	Max
<i>Dependent variables</i>					
Likes	Like count	276.100	1069842	0	19821
Replies	Reply count	96.390	91887.890	1	7214
Retweets	Retweet count	44.750	66004.9	0	6947
<i>Independent variables</i>					
Drives		4.185	25.152	0	37.5
Cognition		6.793	44.913	0	60
Affect		5.612	25.406	0	42.86
Conversational		7.966	46.162	0	50
<i>Control variables</i>					
Word count	Number of words	20.930	197.558	1	194
Hashtags	Number of hashtags	1.472	2.820	0	15
Day	Dummy variables for the day of posting				
Media type	Dummy variables for Media richness of the post				
Followers	Follower count	296076	184973050939	6678	1317576

Unlike Poisson regression, which assumes equi-dispersion, where the mean equals the variable's variance, NBR eases the equi-dispersion assumption and is appropriate to model variables with over-dispersion. Failure to consider over-dispersion may result in a low standard error and hence low significant values for the predictor variables, leading to invalid conclusions.

Further, the NBR model is a multilevel model, as each tweet is nested under a Fintech company. Multilevel models allow us to control and analyse the tweet-level heterogeneities between companies by defining a random effect at the company level. This effectively controls the cluster-level heterogeneity that may arise due to contextual differences, such as the companies' varied goals and associated social media strategies (Sabate *et al.*, 2014). Ignoring the cluster-level heterogeneity and treating the individual outcomes across different groups as a homogenous group will underestimate the coefficients' standard error and overstate its statistical significance. Thus, in multilevel models, the dependent variable is investigated based on the fixed effect of independent variables and a random-intercept effect at the company level. We define the NBR model $y_i \sim \text{NB}(\mu_i)$ following Cameron and Trivedi (1986), where the functional form for the NBR is the log of the count variable predicted with a linear combination of the explanatory variables.

$$\log \mu_i = \eta_i = \beta_{i0} + \beta_{i1}x_{i1} + \dots + \beta_{ik}x_{ik}$$

The present study set forth four hypotheses to examine the effect of language elements on the three measures of OCE using three models.

Thus, for model 1

$$\begin{aligned} \eta_i[\text{Like counts}] = & \beta_0 + \beta_1 \text{Drive words} + \beta_2 \text{Affective language} + \\ & \beta_3 \text{Conversational language} + \beta_4 \text{Tweet length} + \beta_5 \text{Hashtags} + \\ & \beta_6 \text{Day of posting} + \beta_7 \text{Media type} + \delta' \text{Company} + \log \text{Number of followers} \end{aligned}$$

Model 2:

$$\begin{aligned} \eta_i[\text{Reply counts}] = & \beta_0 + \beta_1 \text{Cognitive language} + \beta_2 \text{Affective language} + \\ & \beta_3 \text{Conversational language} + \beta_4 \text{Tweet length} + \beta_5 \text{Hashtags} + \\ & \beta_6 \text{Day of posting} + \beta_7 \text{Media type} + \delta' \text{Company} + \log \text{Number of followers} \end{aligned}$$

Model 3:

$\eta_i[\text{Retweet counts}] = \beta_0 + \beta_1 \text{Drive words} + \beta_2 \text{Cognitive language} +$
 $\beta_3 \text{Affective language} + \beta_4 \text{Conversational language} + \beta_5 \text{Tweet length} +$
 $\beta_6 \text{Hashtags} + \beta_7 \text{Day of posting} + \beta_8 \text{Media type} + \delta' \text{Company} +$
 $\log \text{Number of followers}$
 The term *Company* refers to the vector of Fintech company dummies, and its effects on the
 like counts are captured through the vector σ' . The $\log \text{Number of followers}$ is the offset
 term used to scale the mean.

4. Results

Table VI: Negative Binomial regression model results

	Likes	Replies	Retweets
Intercept	-7.009*** (0.382)	-8.186*** (0.405)	-9.666*** (0.345)
<i>Central Route</i>			
Drives	0.015** (0.005)		0.035*** (0.007)
Cognition		0.012*** (0.004)	-0.013** (0.004)
<i>Peripheral Route</i>			
Affect	0.021*** (0.005)	0.019*** (0.005)	0.014* (0.006)
Conversational	0.034*** (0.005)	0.025*** (0.005)	0.060*** (0.006)
<i>Control Variables</i>			
Word count	-0.003 (0.002)	-0.001 (0.002)	0.015*** (0.003)
Hashtags	0.016 (0.018)	-0.092*** (0.017)	0.061** (0.022)
Day	0.203*** (0.060)	0.118* (0.058)	0.276*** (0.071)
Media type (Ref: Photo)			
Text	0.371*** (0.068)	0.645*** (0.072)	0.205*** (0.086)
Video	0.424*** (0.085)	-0.065 (0.079)	0.149 (0.098)
Link	0.318*** (0.076)	0.321*** (0.074)	0.598*** (0.088)
Conditional R ²	0.61	0.657	0.542

Note: Standard errors are in parentheses. *p < .05; **p < .01; ***p < .001.

Table VI reports the effects of language elements on OCE. Model 1 uses the number of likes
 as the dependent variable, while Model 2 and Model 3 use the number of replies and retweets.
 H1 posited that words which include the psychological process of drives would generate more
 affective engagement on official Fintech Twitter handles. The results of Model 1 show that H1
 was supported for the like count that represents the affective engagement measure ($\beta = 0.015$,

p<0.001). Similarly, more retweets were generated by tweets with drive words (Model 3: $\beta = 0.035$, $p < 0.001$). H2 posited that words that refer to the psychological process of words cognition would generate more cognitive engagement. The results of Model 2 show that H2 was supported for reply count that represents cognitive engagement measures ($\beta = 0.012$, $p < 0.001$). Thus, we found support for H1 and H2, which studied the linguistic dimensions influencing the engagement measures through the central route of persuasion.

H3 posited that words which cover the psychological process of affect would generate more overall engagement. The results of Model 1, Model 2 and Model 3 show that H3 was supported for like count ($\beta = 0.021$, $p < 0.001$), reply count ($\beta = 0.019$, $p < 0.001$), and retweet count ($\beta = 0.014$, $p < 0.05$). H4 posited that words which cover the conversational aspect would generate more overall engagement. The results of Model 1, Model 2 and Model 3 show that H4 was supported for like count ($\beta = 0.034$, $p < 0.001$), reply count ($\beta = 0.025$, $p < 0.001$), and retweet count ($\beta = 0.060$, $p < 0.001$). Thus, we found support for H3 and H4, which studied the linguistic dimensions influencing engagement measures through the peripheral route of persuasion.

5. Discussion

There has been rapid growth in adopting Fintech for fund management over the last few years. Past studies have established the importance of linguistic styles in influencing sourcing (Lee *et al.*, 2019, Rossolini *et al.*, 2021) and the deployment of funds (Herzenstein *et al.*, 2011). We extend the discussion on the influence of language on OCE in the Fintech domain. Our study explores the importance of linguistic style in influencing OCE with communication.

With technology being the backbone of Fintech, we studied communication by Fintech brands in the tech domain by analysing their messages on social media and their resulting consumer engagement. Our findings provide strong support for all four proposed hypotheses. The results suggest the relevance of the dual processing mechanism of ELM as an explanatory theory for

evaluating the OCE with messages posted by Fintech brands. We next discuss each of the findings.

First, our study suggests that using drive words reflecting affiliation, achievement, reward, power, and risk will likely evoke greater traction with users. We believe this is because of the distinctive characteristic of Fintech platforms. Consumers engaging with Fintech platforms may exhibit a higher propensity for messages dealing with risk, reward, achievement and recognition – all sub-categories under the umbrella of drive words. Our results support past findings that engagement of users with new ideas/technology is likely to work better through using drive words such as ones related to achievement/success (Liang and Kee, 2018). The results are in line with findings in different social (Berman *et al.*, 2019; Okunloye *et al.*, 2023) and business contexts (hospitality; Koh *et al.*, 2021) that have suggested a substantial likelihood of drive words positively impacting OCE with social media posts. This engagement seems to stem from a greater elaboration due to higher affective involvement (Voss *et al.*, 2003). This affective involvement is likely to influence the hedonic dimension of an individual's attitude (Voss *et al.*, 2003), particularly in the case of Fintech, where the consumer is likely to have a greater propensity towards risk, reward and achievement. Drive words also elicit emotional responses like fear, excitement or desire from users. Hence, due to this alignment between consumers' propensity and emotions evoked through drive words, individuals are likely to engage more with Fintech messages due to deliberate and effortful thinking.

Secondly, the findings support our hypothesis that cognitive language signalling causality, insights, factual information and explanation provision will likely evoke greater user traction. The risk-reward involved in financial transactions is likely to evoke greater cognitive processing of messages posted by Fintech brands. This engagement seems to stem from a greater elaboration due to higher cognitive involvement (Voss *et al.*, 2003). This cognitive involvement is likely to influence the utilitarian dimension of an individual's attitude (Voss *et*

1 *al.*, 2003), particularly in the case of Fintech, where monetary involvement increases the ask
2 for rational processing of information. Users may respond better to more objective, factual
3 messages and have greater diagnostic value while processing them. The findings support
4 observations by Jeong and Koo (2015) that the objectivity of language content will likely
5 positively impact OCE via the central processing route. Given its emergent nature and
6 monetary associations, audiences may have a greater feeling of uncertainty and risk and seek
7 more diagnostic factual information that carries cognitive cues (Hlee *et al.*, 2021). Factual,
8 objective language content that supports cognitive processing will likely create easy-to-
9 understand, evaluate and actionable cues for an audience still forming their expectations,
10 particularly for emerging ventures like Fintech (Parhankangas and Renko, 2017).

11 Further, as Hlee *et al.*,(2021) noted, objectivity in cognitive language may particularly help in
12 processing messages with greater search/evaluation value. Surprisingly, cognitive words
13 garnered a negative effect on retweet count. Consumer engagement literature on financial
14 institutions has observed cognition to play a crucial role in engaging consumers (Mishra, 2021).
15 A possible explanation for the negative effect of cognitive words in the context of Fintech can
16 be offered through the information overload theory, which details that the increased amount of
17 information sharing beyond the processing capacity limits consumer action (Schultz, 2017).
18 The consumer may perceive posts with increased cognitive words as less understandable and
19 may deter from retweeting the post. Neither the consumers appreciate a post with limited
20 information (Hernández-Ortega *et al.*, 2020). A possible reason for such contradicting results
21 may be an inverted U-shaped relationship between cognitive words and the consumers'
22 engagement on Twitter (Chandrasekaran *et al.*, 2022; Mariani *et al.*, 2016).

23 Thirdly, we found that affective words that convey emotions and reveal the intentions of the
24 message posted by Fintech brands positively impact OCE. Messages posted by Fintech brands
25 may require greater cognitive processing. Consumers who lack expertise in that domain may

1 take refuge in heuristics provided by affective messages (Greifender *et al.*, 2011), and their
2 engagement may be driven by the cues embedded therein. Affective cues have been noted to
3 drive consumers' decision processing (Lee *et al.*, 2019). These heuristic cues provided by
4 affective messages evoke immediate affective responses and are processed via the peripheral
5 route that requires lower processing resources (Ludwig *et al.*, 2013). Newer
6 technologies/platforms/use cases, like Fintech, being difficult to evaluate, affective content
7 may play a signalling role in driving OCE. The influence of affective content is likely to get
8 accentuated even more for those users who lack expertise in Fintech (Cohen *et al.*, 2018). These
9 users are likely to use affective language cues to form the perception of credibility and
10 legitimacy, hence impacting OCE (Lee *et al.*, 2019).

11 Finally, the findings support our hypothesis that Fintech brands using conversational language
12 in social media messages will likely elicit greater OCE. Informal conversational language is
13 perceived to be more relationship-oriented and enhances attraction and trust building (Keeling
14 *et al.*, 2010). Conversational signals are a strong peripheral cue, especially in conditions
15 involving elements of risk and uncertainty. In such cases, the informality of conversational
16 language fosters a sense of "warmth" (Stone and Can, 2020), signalling a higher relationship
17 investment (Jakic *et al.*, 2017). Trust plays a significant role in online financial exchanges
18 (Shneor *et al.*, 2021). Fintech, being a domain that carries both risk and uncertainty, we expect
19 conversational language to suggest higher relationship investment and is essential in building
20 trust (Shneor *et al.*, 2021). Hence, the higher signalling of trust via conversational messages
21 will likely significantly influence consumers' engagement.

22 **6. Conclusion**

23 The current study explored the impact of the linguistic style used in brand-posted social media
24 content on OCE in the Fintech domain. To address our primary Research question ("What is
25 the impact of linguistic features of a social media message from Fintech brands on OCE?"), we

reviewed past literature and framed our conceptual model and hypotheses. These hypotheses were then tested using tweets from 10 leading Fintech unicorns in India.

Our study finds that using drive words and a cognitive language in Fintech messages increases OCE via the central route of information processing. Additionally, affective words and conversational language in Fintech messages drive OCE through the peripheral route of information processing. These findings indicate the relevance of the dual processing mechanism of ELM as an explanatory theory for evaluating OCE for messages posted by Fintech brands. Our study findings extend the literature on social media engagement for brands, especially for technology fields at the early stage of consumer adoption. We next discuss the theoretical and managerial implications of our study.

6.1. Theoretical implications

This study attempted to make multiple theoretical contributions to the existing literature. Our study augments the literature on OCE by divulging what message characteristics motivate consumers to engage on social media (Gorodnichenko *et al.*, 2021). By empirically substantiating the impact of linguistic characteristics on OCE, our study also contributes to broader research on the effect of message characteristics in generating greater brand engagement in mediated online conversations. While the focus of prior research was primarily on understanding what is communicated and the associated presentation method (Lee and Kahle, 2016), we refer to the dual processing by ELM route to conceptually understand the central and peripheral pathways of message processing based on linguistic characteristics. A social media message building on suitable linguistic characteristics is essential for enhancing OCE (Deng *et al.*, 2021b).

The study advances the current research on OCE by outlining a method to examine social media posts to unveil their linguistic style. We thus extend extant research in two important ways.

1 First, Ludwig *et al.*, (2013) propose that modifications in communication style can prompt
2 increased OCE, which suggests that linguistic styles could be a good predictor of OCE.
3 However, the scope of the research has been restricted to online reviews (Ludwig *et al.*, 2013;
4 Lee *et al.*, 2019); we extrapolate to derive the effect of linguistic style on a social media
5 platform. We thus show that in a social media brand page setting, the impact extends beyond
6 the content type and media type to include linguistic style as a key predictor for OCE. Second,
7 OCE is context-specific (Annamalai *et al.*, 2021), and significantly fewer studies are conducted
8 in the financial sector, such as crowdfunding (Zhu, 2022), financial inclusion (Lagna and
9 Ravishankar, 2022) and cryptocurrency price prediction (Mai *et al.*, 2018). The current
10 research theoretically contributes by detailing the nuanced relationship between the affective
11 and cognitive linguistic elements and OCE in the Fintech context.

12 Next, our study results for social media messages in the Fintech domain support the relevance
13 of ELM, observed earlier in other domains (Hagemann and Abramova, 2023). Prior studies
14 mainly used ELM to investigate consumers' information processing of advertisements (Rollins
15 and Bhutada, 2014), electronic health record adoption (Angst and Agarwal, 2009) and
16 perceived values on e-commerce (Chen and Lee, 2008). Only a few studies have used ELM to
17 examine consumer behaviours in social media (Annamalai *et al.*, 2021; Deng *et al.*, 2021a). To
18 our knowledge, this research was one of the initial attempts to apply ELM in the Fintech
19 domain. Especially the linguistic style in Fintech enables us to comprehensively examine the
20 distinct psychological processes and the information processing routes distinct from other
21 contexts (e.g., business-to-business). As such, this study, on the one hand, made a salient
22 contribution to the linguistic literature and, on the other hand, confirmed the perspective of
23 ELM with empirical results, extending its application in multiple ways.

24 This research empirically demarcates the consumers' behavioural responses as affective and
25 cognitive measures. The study results further indicate that drive words and cognitive words in

the Fintech shared tweets influence the like count and reply count, respectively, that represent the consumers' affective and cognitive engagement behaviour in the same order via the central route. Further, affective and conversational words influence the consumers' behavioural dimensions via the peripheral route. Hence, this study provided valuable knowledge to better interpret the behaviour of the consumers of Fintech tweets based on psychological processes. Finally, at a broader level, our study highlights the explanatory role of ELM in garnering consumer engagement in fields that are at the initial stages of consumer adoption. Depending on consumers' different capabilities and motivations, their information processing may take either a cognitive or an effective route or a combination of both.

6.2 Managerial implications

Given the highly competitive scenario in the Fintech industry in India and the need to use their marketing budgets most intelligently, the major Fintech players need effective ways of leveraging social media channels for increasing their brand's OCE. In this context, our study has key managerial implications for marketing managers of Fintech companies. First, our findings guide fintech firms' social media marketing managers to choose an appropriate linguistic style in their posts to improve OCE. Our study highlights that appropriate linguistic models that tap into the consumers' central and peripheral processing routes need to be utilized to engage online with customers. This is because the customers may be trying to satisfy either of (or both) information and emotional needs when they are faced with social media posts from Fintech companies. This key managerial implication is explained below.

The study combines linguistic theories with a Fintech communication model comprising dual routes for information processing and validates the linguistic influence on OCE empirically. The research highlights the significance of studying the linguistic multimodality (Deng *et al.*, 2021b) underlying social media messages. First, the numerous modal elements in brand messages influence online consumers' information processing routes. Subsequently, the

information processing routes drive the OCE behaviours. Being multimodal, the functional features of cognitive language and drive words are centrally processed by online consumers. The findings illustrate that Fintech brands could deliver functional appeals through informational language driving cognition. Rationally, consumers will likely hold a practical motive for engaging with informative posts. By including drive words, Fintech brands could enhance OCE through the central processing route, and the interpersonal features of the affective and conversational language are peripherally processed by online consumers. The findings illustrate that Fintech brands could render emotional appeals through linguistic elements such as affective and conversational language. The results of the peripheral routes support literature acknowledging the impact of emotional appeals in driving brand equity (Lynch and De Chernatony, 2004). Using linguistic features also facilitates peripheral processing by building a personal connection between the consumer and the brand to enhance OCE (Cortez *et al.*, 2020), specifically affective and conversational language. Thus, the findings illustrate that Fintech brands could convey emotional appeals through linguistic features and informational content. The implication for Fintech marketing is that it highlights that Fintech brand posts are likely to be read by online consumers with motives ranging from emotional to rational consideration (Deng *et al.*, 2021b). Thus, the results support the appropriate design and use of linguistic features to facilitate OCE through the brand post's central and peripheral route processing.

Given that the consumers' personalities can be assessed through linguistic differences (Pennebaker and King, 1999), brands must use a language style online consumers prefer to build a distinct and consistent identity (Michaelidou *et al.*, 2011). In this regard, the findings have implications by recommending a friend-like voice (by including conversational language cues) in Fintech social media messages. Further, the results suggest consumers are more likely to engage with increased cognitive language and drive words. It reminds us that, although

Fintech consumers respond to a strong emotional and interpersonal connection, the brands must cater to the informational need through cognitive language for enhanced engagement. Thus, our results indicate that brands must manage linguistic style when planning social media-based communication with consumers.

6.3 Limitations and future research

The current research investigates the effect of social media post linguistic features on Fintech brand engagement. The study addresses linguistic features in the Fintech brand social media post. The research relied upon tweets that the brands primarily regulate. It would be interesting to study user-generated content, such as tweets and replies on Twitter (Saura *et al.*, 2021; Saura *et al.*, 2022). Social listening of this massive data will significantly benefit mass surveillance (Ribeiro-Navarrete *et al.*, 2021). It would be interesting to examine further the effectiveness of other modal elements used to design the post, such as the textual content type and media type. This will provide a comprehensive understanding of what is being said and how it is being said in social media communication. Further, studying these effects provides a profound understanding of the *modus operandi* of two information processing routes in Fintech brand communication. Also, it provides tactical guidance for Fintech marketers to increase OCE. The study relies on data from Twitter alone. Given that consumers use different social media platforms for different purposes (Kietzmann *et al.*, 2012), examining the linguistic influences of brand posts on other social media platforms, such as LinkedIn and Facebook, would be interesting. Such investigation will provide meaningful guidance for Fintech brands to devise cross-platform strategies. Finally, this study focuses solely on the Indian Fintech industry, and further research should aim to examine the global Fintech market for a more comprehensive analysis.

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