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E-Marketplace Strategies to Drive Popularity, Virality, and Engagement on Twitter

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ABSTRACT

The purpose of this study is to investigate e-marketplace strategies for increasing popularity, virality, and engagement on Twitter, as well as the moderating impact of e-marketplaces. This study collected Twitter data from two e-marketplaces posted within the past six months. I used Twitter data mining tools, an intent mining tool, Generative AI, and a spreadsheet to extract content strategies (including length, interactivity, novelty, consistency, and content features), media strategies (based on vividness features), and scheduling strategies (focused on timing features). Hierarchical regressions were applied to investigate relationships between these strategies and customer engagement. Length, interactivity (having URLs), novelty (price, place, promotion, physical evidence information), content (message intent: sentiment), vividness (media type: texts and photos) decrease popularity/ virality/ engagement, while interactivity (hashtags and mentions), novelty (people), consistency (brand mentioned), vividness (having media URLs), timing (Mon-Fri, except Thu) increase them. E-marketplace brands are also significant moderators. This work reflects e-marketplace strategies each brand employs, guides them to adjust their content, media, and scheduling strategies to gain more likes and retweets, and reveals the impact of their brands as a moderator. This study employed novel data collection and processing techniques, along with introducing unique content themes (7Ps) to examine firm-generated content in the e-marketplace context, which expands knowledge in social media marketing literature.

Keywords: popularity, virality, engagement, social media strategy, Twitter, e-marketplace, service marketing-mix

1. INTRODUCTION

E-commerce has become the primary medium for businesses to achieve their sales goals, especially after the COVID-19 pandemic [1-3]. According to Statista Inc. [4], the e-commerce market in Thailand is projected to generate $11.68 billion in revenue in 2024 and is expected to grow to $19.4 billion by 2029. E-marketplaces are the solution for current and future e-commerce markets [5]. They are dominant platforms for buying and selling goods and services [6]. They are also the preferred online shopping platforms for Thai consumers [2, 7, 8].

Social media (SM) affects customers' use of e-marketplaces [9] and enhances transparency and trust in e-marketplaces [6]. Social media marketing (SMM) also increases their willingness to purchase from small and medium retailers [10]. Thais are very active on social media. In 2022, they spent nearly three hours per day on social media, creating an opportunity for businesses to reach them [8]. Businesses combine e-commerce and SM to distribute information, increase brand awareness, and build a fanbase [11, 12]. Consumer involvement and engagement support e-commerce success [11] as well as the continuous usage intention [13]. SMM plays a critical role in fostering customer engagement in e-marketplaces, but how it can specifically bolster e-marketplaces' performance has been unexplored in the literature [6].

Active engagement on SM enables companies to build customer relationships, increase brand loyalty, generate traffic to online platforms, and raise customer retention [14-22]. However, creating effective SM content is challenging because companies face difficulties understanding what drives customer engagement [23-25].

Twitter is a powerful SM for improving business performance [19, 26]. Most businesses use it for marketing purposes [12, 26]. Marketers can tweet information about their brands, products, services, or promotions [27]. Twitter is a popular and effective tool for brand engagement [12, 18, 27-30]. Companies must comprehend its dynamic to harness its full potential and drive e-marketplace performance [31]. Social electronic word-of-mouth (e-WOM) significantly drives customer trust and customer repurchase intention [32]. This work evaluates popularity using likes or favorites (FAV) and measures virality by retweets (RT). Engagement combines both [33-38].

Likes indicate the appreciation of users on a tweet [17]. Retweets facilitate the spread of information quickly [17, 39-41].

There are differences in customer engagement with tweets between industries and brands, so marketers have to know how tweet features support the propagation of brand messages [39, 42-44], particularly for marketer-generated content (MGC) [12, 27, 45, 46] on Twitter [26] in the e-commerce context [47].

Research is needed to explore content strategies on different SMs [26, 48]. Understanding of content-related factors driving engagement is still poor [46]. In the service marketing mix/e-marketing mix, the traditional 4Ps are expanded to 7Ps, which have become a fundamental strategy for online environments [45, 49]. Customers choose brands based on this information [50, 51]. SM can also optimize the 7Ps marketing mix implementation. Marketing strategies can be boosted by utilizing the 7Ps marketing mix as well [52].

Few studies use data mining techniques in this field [53]. Brand message intention has received less attention than customer reviews/ tweets [11, 30, 54]. Message sentiment could impact retweets [55, 56]. Besides, deductive coding to identify content themes is often burdensome [57].

Therefore, this work answers the following questions: RQ1: How do e-marketplace strategies in terms of content, media, and scheduling strategies impact popularity, virality, and customer engagement? RQ2: How does the moderating effect of an e-marketplace brand influence the formation of popularity, virality, and engagement? This study uses data mining techniques to identify message intention and sentiment, along with large language models (LLMs) to extract 7Ps information from the tweets of two e-marketplaces in Thailand.

2. THEORY AND HYPOTHESIS DEVELOPMENT

2.1 Social Media Theories

2.1.1 Social Media Engagement Theory (SMET) and Social Media Communication Theory

Social media engagement theory holds that the application of social media enables organizations to communicate with customers and reach organizational goals [58]. It is a theory meant for interpreting customer relationships through user interaction and engagement on digital platforms provided by organizations [3]. According to SMET, user experience (encompassing both social interactions among users and the technical features of an SM platform) impacts user engagement. Social interactions, i.e., personalization, critical mass, and risk, and technical features significantly impact user engagement. Higher user engagement leads to greater usage of SM platforms. [58-61]. Social media engagement consists of affective, behavioral, and cognitive components. Behavioral engagement also enhances affective engagement [62]. Past research leveraging SMET indicates that content type and the timing of marketing campaigns help build a strong brand [58]. SMET also highlights that customer engagement is influenced by message characteristics [63]. SM engagement interacts with content likability, affecting content credibility on mobile social networks. Highly likable content results in high user engagement [60].

SMET builds on social media communication theory, which posits that B2B communications encode messages on SM platforms with specific message sources and content. These messages, as interpreted by customers, influence their engagement with B2B firms. Therefore, B2B firms can employ different messaging strategies to shape customer engagement [63].

2.1.2 Uses and Gratifications Theory (UGT) and Dual Processing Theory

Uses and gratifications address how individuals choose media to fulfill their needs, such as the need for information seeking, enabling them to realize gratifications [61, 64]. UGT indicates the need to understand the role of message content in affecting its consumption. Content must be designed to create value for consumers to build higher levels of engagement. UGT is also a framework to understand an individual’s motivation for seeking a specific type of content within SM settings, i.e., informative content, remunerative content, entertaining content, and relational content. Liking and sharing are forms of consumers' SM engagement behaviors that represent contributing [64].

Dual processing theory explains how rational and emotional content leads to engagement behavior in SM settings. Rational appeals include informational and remunerative content, e.g., product specifications, features, performance, and other tangible cues, while emotional or affective appeals comprise entertaining and relational content focusing on stimulating emotions associated with the brand or product [64]. The 7Ps marketing mix could be categorized as rational appeals.

2.2 The Linkage between 7Ps and Social Media Strategies

Cahyonoa, et al. [52] analyzed the perception of Twitter users regarding SMM attempts by Indonesian Islamic banks. The perception was assessed based on the 7Ps marketing mix. Findings reveal that the 'people' aspect received the most responses from Islamic bank customers. Positive comments were given about the staff's attitude, professional appearance, and courteous customer service, while negative ones were about long queues and convoluted service. Findings point out that improving marketing strategies can establish positive perceptions of Islamic banks. As customers become more sophisticated, 7Ps strategies may be required instead of 4Ps strategies. Social media can optimize the implementation of these 7Ps strategies.

Fauzi, et al. [65] also examine smart digital marketing on Twitter using the 7Ps marketing mix to assess customer perceptions and compare the most prominent conventional and Sharia banks in Indonesia. Their findings show an extremely imbalanced marketing approach that focuses solely on the 'process' element, leaving other marketing elements insufficiently managed and optimized. However, among the 7Ps, only 'process' satisfies the benchmark, while 'people' almost meet the reference benchmark.

Sukmana, et al. [66] investigated the 7Ps marketing mix influencing the preferences of restaurant patrons and how these marketing mix elements are articulated in online reviews on Google Maps. The results show that customers predominantly talked about 'product' and 'price,' whereas other elements, i.e., ‘place,’ ‘promotion,’ ‘process,’ ‘people,’ and ‘physical evidence,’ had a lower percentage of discussions and were only mentioned in relation to specific ratings, which means they do not have a significant impact on customer reviews.

Christanto, et al. [67] investigated the marketing strategies on Instagram (IG) and TikTok using the 7Ps framework. Findings highlight the significance of ‘place’ in IG and TikTok marketing strategies, as both platforms focus on user-friendly interfaces, secure and timely deliveries, and convenient product selection. By aligning these elements with customer preferences, both platforms can enhance customer engagement as well as satisfaction, which can drive sales growth.

Szymkowiak, et al. [68] explored how different types of content impact communication efficiency on social media using the 7Ps marketing mix. The results showed that product posts have a higher number of reactions compared to non-product posts. Product posts draw more comments than other types of posts. They also get more clicks on their photos than other types of posts.

2.3 Social Media Strategies

Iqbal Khan and Ahmad [69] identify three strategies that affect online engagement: content, media, and scheduling strategies. Message features of tweets result in information diffusion [26]. Companies should formulate content strategies that are suitable most for them [70]. Content strategies include length, interactivity, novelty, consistency, and content features. Media strategies incorporate vividness features, while scheduling strategies are timing and frequency features [70].

2.3.1 Content Strategies

According to UGT and Dual Processing Theory, in the study of Dolan, et al. [64], informational content significantly increases social media engagement behaviors (SMEB) in terms of consumption, likes, and shares. Remuneration content significantly increases SMEB (consumption, likes, and shares). Entertainment and relational content significantly affect SMEB in the form of consumption.

Length Features: Tweet Length Length features include the number of words or characters [70]. The number of words in a tweet increases RT [71]. The number of characters determines retweets, likes, and replies [72]. Word count increases likes and RT, while character count decreases them [73]. Length of Twitter use is associated with followers' engagement in eWOM behaviors [30]. Content length improves online engagement on Twitter [69]. Body length is one of the relative features important in engagement [33]. Post length positively affects brand engagement [42]. Lengthy tweets obtain RT [53]. On the contrary, the length of tweets decreases customer engagement [44]. Based on these findings, I have developed the following hypothesis:

H1: Tweet Length influences a) popularity, b) virality, and c) engagement.

Interactivity Features: Hashtags, Mentions, Having URL The interactivity of search engine marketing implementation is significantly correlated with purchase intention [74]. Interactivity features include hashtags, links, and mentions [69, 70]. They are the relative feature importance on engagement [33] and positively affect RT [75]. Hashtags increase likes and RT, while links decrease them. Hashtags and weblinks positively impact likes and RT, whereas mentions negatively affect them [28]. Hashtags and mentions increase online engagement on Twitter [69, 76]. Mentions and URLs influence separating viral from non-viral tweets [77]. URLs and hashtags, but not mentions, positively influence on customer engagement [44]. Unlike URLs, hashtags contribute to tweet popularity [78]. An increase in hashtags and mentions could decrease RT [71]. Hashtags and URLs negatively influence brand engagement [42].

Hashtags increase tweet diffusion [53] and consumer engagement [79]. Users writing hashtags get FAV and RT [53]. Hashtags improve the likelihood of having one FAV/ RT [46]. Yet, the presence of a hashtag lowers both likes and shares [80]. Mentions influence engagement [18] regarding likes and retweets [53]. Mentions influence sharing [81], but they are negatively associated with engagement [15]. They can lower likes [73]. URLs could increase RT [82]. Hyperlinks positively [27, 83] and negatively affect FAV and RT [12]. The number of links improves forward, but it leads to fewer comments and likes [84]. Hence, I have set the following hypotheses for verification:

H2: Hashtags influence a) popularity, b) virality, and c) engagement.

H3: Mentions influence a) popularity, b) virality, and c) engagement.

H4: URL influences a) popularity, b) virality, and c) engagement.

Novelty Features: Unique Content (7Ps) Information quality improves both customer trust and repurchase intention [32]. The intensity of informational messages posted on mini-program channels enhances the role of mini-program channel use in consumers’ purchase frequency in the e-marketplace [85]. Novelty features represent unique content [70]. Content orientation/ content type impacts engagement [69, 86-88]. In this study, unique content means content relating to 7Ps. A marketing mix (MM) is a tactic that effectively markets products or services to consumers, which influences their purchase decisions [89]. The 4Ps marketing mix (product, price, place, promotion) is expanded to the service marketing mix (7Ps) by adding people, process, and physical evidence [5, 90-92]. The 7Ps influence young consumer buying interest [93] and brand trust [94]. Place, people, physical evidence, and process positively affect customers [95]. Promotion, place, and physical evidence significantly increase customer purchase intention in live streaming shopping (LSS) [45]. Price, promotion, place, physical evidence, and process affect purchase decisions about agricultural products in the e-marketplace [89]. Product information can increase the purchase interest of potential customers [96]. Customers’ intention to buy is influenced by product information, delivery costs, store status, and discounts [1]. Promotion has a significant influence on customer use of online e-marketplaces [9]. Product promotion influences customer brand preference [50]. Unlike brand messages promoting brands, products, or services, brand messages with sweepstakes or giveaways get more likes and RT [97]. Price promotions induce brand awareness and usage [98]. Posts about promotion receive high likes and comments [99]. However, in the study by Weerawatnodom, et al. [12], discount or promotional information decreases FAV and RT. Campaigns affect favorites [27]. Competitive actions for a firm to strengthen its relatively competitive position are pricing, marketing, new product, capacity and scale-related, service and operations and legal actions [100]. Therefore, I test the following hypothesis:

H5: Marketing-mix information influences a) popularity, b) virality, and c) engagement.

Consistency Features: Brand Mentioned Consistency features are brand name, logo, and value proposition [70]. SM brand communication increases SM brand engagement [21]. Brand centrality influences both FAV and RT [27].

Past research reveals that users tend to interact, e.g., comment and share information on a brand when a tweet primarily focuses on the brand [30]. Posts that include brand names create a sense of inclusion for customers, leading to higher likability [37]. On the contrary, high brand prominence in ads decreases sharing [101]. In airline tweets, the brand mentioned negatively affects likes and RT [76]. Tweets with more mentions of the organization receive more RT [71]. Consumers' motivation to share brand messages is more salient when the messages contain corporate brand names. Their use significantly increases likes and comments, particularly for services [102]. Based on these discussions, I develop the following hypothesis:

H6: Brand mentioned influences a) popularity, b) virality, and c) engagement.

Content Features: Message Intent Content features incorporate content type, sentiment, and valence [70]. In this work, content features refer to message intent. Past research classified content as information-sharing, emotion-evoking, and action-inducing [16, 103]. Information-related posts obtain likes, while action-related posts generate more shares [82]. Call-to-action posts get medium likeability [37]. Retweet request predicts RT count [39]. Past research identifies six intent categories for tweets (Food & Drink, Travel, Career & Education, Goods & Services, Event & Activities, and Trifle). In contrast, others identify commercial intent regarding buying and selling intention [104, 105].

Sentiment analysis is a branch of text mining [106, 107]. Sentiment analysis is commonly used to quantify positive and negative sentiments about a brand [106, 108, 109]. It is critical for both e-marketplaces in this study so that the companies can generate marketing plans to win more customers and boost their happiness [110]. Sentiment is a relative feature important in engagement [33]. Strong sentiments (positive or negative) obtain likes and RT [53]. Nevertheless, sentiment is negatively correlated with likes, comments, and retweets [111]. Positive words increase engagement [44]. Tweet emotional positivity increases likes, but decreases RT [28]. In airline tweets, positive/ negative sentiment receives more RT, while positive sentiment also gets more likes [76]. Negative sentiment determines retweets and likes [72, 78]. As a result, I propose the following hypothesis:

H7: Message intent influences a) popularity, b) virality, and c) engagement.

2.3.2 Media Strategies

Vividness Features: Having Media URL, Media Type Vividness features could be media links and type [69, 70]. Vividness increases engagement, likes, and reactions [23]. Information richness of videos and images increases forwards, comments, and likes [84]. Consumers are more engaged with richer media types [24]. Using GIFs, photos, and videos boosts brand engagement [42]. Images and videos improve likes and comments for SM messages [102], brand engagement (likes, shares) [80], FAV and RT [112], and online engagement on Twitter [69]. SM is used to boost sales by attracting potential customers through videos, images, and links [96]. Visual marketing is a growing trend for increasing online engagement [113]. A picture increases likes, comments, and shares, while more than one picture enhances likes and comments [70]. Pictures affect both FAV and RT [27, 76]. The number of photos in a tweet predicts RT [39]. Tweets containing images generate more FAV and RT [114]. Images negatively impact consumer engagement [79]. Fan engagement is higher for tweets sharing photos [86]. Videos positively affect likes and shares [70, 115] and RT [12]. Based on this, I present the following hypotheses:

H8: Media URL influences a) popularity, b) virality, and c) engagement.

H9: Media Type influences a) popularity, b) virality, and c) engagement.

2.3.3 Scheduling Strategies

Timing Features: Day Timing features can be the time of the day or day of the week [69, 70]. Day of year improves likes, whereas day of week decreases likes and RT [73]. Past studies show contradictory results. Research on digital advertising and marketing indicated that the percentage of consumers who clicked links decreased on weekends. Another study stated that posting on weekdays decreased likes and comments, while a different study found that weekdays increased comments [116]. Posted days impact citizens' engagement [117] and are a relative feature important to engagement [33]. The day of the week plays a significant role in Twitter engagement [15, 69]. SM user activities differ between weekdays and weekends [42]. Ibrahim, et al. [118] specify that weekends are when most people are on Twitter. Tweets posted on the weekends gain more brand engagement than those posted during weekdays [80]. Weekend posts increase RT [119]. Published days significantly affect the interaction between treatment and pre-social engagement in the study by Xue, et al. [120]. Daily wise also significantly drives post reach [121]. The results of the random forest tree algorithms in the study by Aydin, et al. [122] reveal the significant role of days between posts in impacting total engagement. Thus, I set the following hypothesis:

H10: Day influences a) popularity, b) virality, and c) engagement.

2.4 E-Marketplace Differences

Brand equity is the customer's assessment of the brand. It significantly positively affects trust and customer loyalty [123]. According to Soboleva, et al. [39], there are vast differences in consumer engagement with tweets across brands, with even leading brands experiencing low engagement, such as RT. Therefore, I formulate the following hypothesis:

H11: An e-marketplace brand moderates the relationships between independent variables and a) popularity, b) virality, and c) engagement.

3. METHOD

According to Yin, et al. [110], ACom and BCom are e-commerce platforms that focus on providing users with an effective online marketplace for business-to-customer (B2C) transactions. They are also leading players in most markets throughout the Southeast Asia region. This study targeted two leading and widely used e-marketplaces in Thailand, referred to as ACom and BCom. In sum, they had almost 95 million visits monthly in the first quarter of 2022 [7]. Tweets from the official accounts of these e-marketplaces were collected using a free Twitter scraper tool called Vicinitas. Generally, the tool allowed us to download the most recent 3,200 tweets from any public Twitter profile [124]. Several past studies have applied the tool [124-131]. After removing missing tweets, retweets, replies, and non-Thai records, and focusing on tweets from the same 6-month period, I retained 2,196 tweets. These tweets were published over a six-month period, providing a longitudinal aspect to the data and helping mitigate concerns about generalizability [24].

Engagement behavior can be expressed through liking, commenting, sharing, and viewing brand content. Social media engagement consists of three levels: consumption (e.g., viewing brand-related audio, video, or pictures), contribution (e.g., liking, sharing, and commenting on brand-related content), and creation (e.g., publishing brand-related content, uploading brand-related videos, pictures, or audio, or writing brand-related articles) [132]. Dependent variables were popularity (log FAV), virality (log RT), and engagement (log ENGAGE). The engagement was the sum of FAV and RT. The calculations for popularity, virality, and engagement were adapted from previous works [33, 34, 126, 133-135], which were suitable for message-level analysis. This work log transformed FAV and RT to reduce skewness. Independent variables in the primary regression model were Tweet Length, Hashtags, Mentions, Having URL, Having Media URL, Media Type, 7Ps, Brand Mentioned, Message Intent, and Days. E-Marketplace (ACom) was investigated as moderator, whereas Passed Days were a control variable since the age of tweets affected FAV and RT [46]. Having URL, having media URL, media types, 7Ps, message intent, day, and e-marketplace brand were dummy variables. Unlike media types and days, message intent and 7Ps were not mutually exclusive.

This study applied a spreadsheet's functions to determine tweet length, having URL, having media URL, media type, brand mentioned, and day, while adopting intent mining from AI for Thai to extract message intent (as well as sentiments) [136] [137] and LLM (Chat GPT 3.5) to do deductive coding and identify tweets related to 7Ps. ChatGPT is a powerful language model with context-aware responses. GPT-3.5 also provides advanced natural language processing capabilities to perform tasks such as processing large datasets with accuracy and relevance [138-140]. It codes at a level of agreement comparable to human coders or experts [57, 138, 141]. Researchers have used ChatGPT to automate content analysis in literature, expediting its time-consuming process [57, 138, 140-142]. I applied descriptive statistics for data analysis. This work employed hierarchical regression to test the hypotheses.

For the data preprocessing procedures, tweets in Thai were automatically translated using Google Translate, then all were converted to lowercase using a function in Microsoft Excel. Tweets were classified into the 7Ps using the following prompt: "Check whether these sentences mentioning product, price, place, promotion, people, process, and physical evidence. Show the results in the tabula format, which first column shows sentence number. Extract keywords from the sentences representing 7Ps (if any) in the table. If blank, add sign -:”.

For the reliability and validity of ChatGPT, 100 tweets from ACom and 100 tweets from BCom were used to extract the 7Ps using another AI tool (Gemini) with the same prompt. Cohen's kappa coefficients were then calculated to evaluate inter-rater reliability for qualitative (categorical) items. The results revealed moderate agreement for product and price, fair agreement for people, and slight agreement for physical evidence. Compared to human classification, using another AI model for verification offers a more scalable and consistent approach, minimizing human biases and subjective variations. While human raters might interpret the tweets differently based on personal experience or contextual understanding, an AI-based cross-checking process ensures a standardized comparison of outputs. However, I recognize the limitations of AI models in handling nuanced or context-dependent interpretations, which is why further refinements in the prompt design and additional validation steps may be necessary.

Moreover, word clouds were applied to portray major keywords for each marketing mix. The results identified main keywords for each marketing mix, including, for instance: ‘products’, ‘'bag’, ‘skincare’, ‘polaroid’, and ‘items’ for product; ‘price’, ‘coupons’, ‘free’, and ‘cheap’ for price; ‘Acom’, ‘BCom’, ‘online’, ‘platform’, and ‘app’ for place; ‘code’, ‘giveaway’, ‘promotion’, ‘discount’, and ‘event’ for promotion; ‘bbillkin’, ‘admin’, ‘namneung’, and ‘ppkritt’ for people; ‘watching’, ‘participating’, ‘shopping’, and ‘announcement’ for process; and ‘image’, ‘links’, and ‘URL’ for physical evidence, all of which align with the respective 7Ps categories.

4. FINDINGS

4.1 Descriptive Statistics

The means (standard deviations) for the variables are as follows: passed days 101.37 (54.126), tweet length 190.31 (83.875), hashtags 2.72 (2.201), and mentions 0.11 (0.482). Other independent variables are dummy variables. There were 1,142 tweets from Acom and 1,054 tweets from BCom. ACom had 283,716 followers, while BCom had 170,501 followers. ACom gained less average popularity (556 FAVs per tweet) and engagement (1,240 ENGAGEs per tweet) than BCom (723 FAVs and 1,372 ENGAGEs per tweet) but received more average virality (684 RTs per tweet) than BCom (649 RTs per tweet). Generally, BCom posted longer messages (218 characters), used more hashtags (3 hashtags per tweet), and included more mentions (0.2 mentions per tweet) than ACom (164 characters, two hashtags per tweet, and 0.0 mentions per tweet). On the contrary, ACom's tweets contained more URLs (0.7 URLs per tweet) and media URLs (0.8 media URLs per tweet) than BCom's tweets (0.5 URLs and 0.7 media URLs per tweet). For 7Ps, both ACom (50.9%) and BCom (80.6%) utilized promotional content the most. ACom also talked about physical evidence (44.2%), products (38.3%), and people (37.7%), whereas BCom tweeted about processes (66.6%), products (65.3%), and physical evidence (64.0%). Both rarely tweeted about the price compared to other Ps. ACom mentioned their brand names in each tweet more often than BCom (2.0 times vs. 1.6 times per tweet). In line with the study by Yin, et al. [110], BCom users share more about promotions, place (online store), and products, while ACom users discuss promotions, contests, rewards, and personal experiences on the platform. ACom also hosted a sale and a giveaway contest. Tweet intention from both e-marketplaces was mainly related to sentiment (64.6% for ACom and 84.0% for BCom), questions (31.8% for ACom and 33.0% for BCom), announcement (20.1% for ACom and 24.1% for BCom), and request (16.7% for ACom and 16.6% for BCom) respectively. Both used positive tones the most (47.1% for ACom and 70.0% for BCom) than neutral (38.6% for ACom and 21.3% for BCom) and negative tones (14.3% for ACom and 8.8% for BCom). From their users, Yin, et al. [110] indicated that both companies received more positive tweets than negative ones, meaning SM users shared more positive opinions about ACom and BCom. For media, ACom extensively used photos (66.0%), while BCom frequently used both videos (37.5%) and images (36.8%). Both e-marketplaces also used text (around 25-26%). ACom used a small number of animated GIFs (0.18%), while BCom did not (0.00%). ACom frequently posted on Friday (26.8%), Thursday (15.2%), and Monday (14.7%), while BCom tweeted on Monday (18.1%), Friday (17.4%), and Wednesday (16.4%). Both ACom and BCom rarely post on weekends. Of 6 months from November to April, ACom posted more on December (27.2%), November (25.6%), and

March (22.2%), whereas BCom often posted on March (29.5%), December (20.1%), and November (19.4%).

4.2 Hypothesis Testing

I conducted hierarchical regression analyses to test the moderator effects, as recommended [143]. As shown in Table 1, three models consisted of the model with control variables, the basic model, and the interaction model. The models in the first step revealed 2.0%, 2.6%, and 2.1% of the explained variances in popularity, virality, and engagement, respectively. Step 2 added all proposed antecedents and a moderator into models, revealing 33.6%, 33.0%, and 33.2% of the explained variance in popularity, virality, and engagement. In this step, tweet length (-), hashtags, mentions, having URL (-), having media URL, media type (photo) (-), place (-), promotion (-), people, physical evidence (-), brand mentioned, message intent (sentiment) (-), day (Mon, Wed, Fri), and e-marketplace (ACom) (-) had significant impacts on popularity. Tweet length (-), hashtags, mentions, having URL (-), having media URL, media type (text, photo) (-), price (-), place (-), people, physical evidence (-), brand mentioned, message intent (sentiment) (-), day (Mon, Tue, Wed, and Fri) had a significant influence on virality. Tweet length (-), hashtags, mentions, having URL (-), having media URL, media type (text, photo) (-), place (-), promotion (-), people, physical evidence (-), brand mentioned, message intent (sentiment) (-), Day (Mon, Tue, Wed, and Fri) had significant effects on engagement. Step 3 investigated the interaction effects. The interaction effects of e-marketplace (ACom) and tweet length (-), hashtags, mentions, having URL (-), price (-), brand mentioned, message intent (announcement), and day (Fri and Sat) on popularity were significant. The moderating effects of e-marketplace (ACom) on the relationships between tweet length (-), hashtags, having URL (-), product, price (-), place (-), people (-), process, message intent (announcement) and virality were significant. E-marketplace (ACom) significantly moderated the relationships between tweet length (-), hashtags, having a URL (-), product, price (-), place (-), message intent (announcement), day (Fri and Sat), and engagement. The increased R-square value due to the inclusion of interaction terms for the popularity, virality, and engagement model were .047, .046, and .045, respectively. The small number of increased R-square of interaction terms was typical in the literature [144].

In sum, there was significant evidence at the 0.05 level to support hypotheses: *H1a-H1c*, *H2a-H2c*, *H3a-H3c*, *H4a-H4c*, *H6a-H6c*, and *H8a-H8c* and partially support hypotheses: *H5a-H5c, H7a-H7c, H9a-H9c, H10a-H10c*, and *H11a-H11c*.

Table 1. The Hierarchical Regression Analysis for Variables Predicting Log Popularity, Virality, and Engagement (n = 2196)

Variables	DV: Popularity Step 1		DV: Popularity Step 2		DV: Popularity Step 3		DV: Virality Step 1		DV: Virality Step 2		DV: Virality Step 3		DV: Engagement Step 1		DV: Engagement Step 2		DV: Engagement Step 3	
	Beta	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*
Passed Days	.143***	6.737	.077***	4.071	.042*	2.056	.162***	7.567	.068***	3.543	.040	1.929	.148***	6.980	.068***	3.575	.036	1.787
Tweet Length			-.235***	-6.872	-.143**	-2.937			-.250***	-7.209	-.147**	-2.947			-.253***	-7.412	-.161**	-3.285
Hashtags			.147***	5.927	.002	.056			.096***	3.807	-.047	-1.443			.123***	4.942	-.016	-.489
Mentions			.040*	2.064	.038	1.849			.050*	2.575	.048*	2.326			.042*	2.175	.042*	2.037
Having URL			-.155***	-6.978	-.051	-1.655			-.125***	-5.557	-.055	-1.742			-.136***	-6.121	-.046	-1.484
Having Media URL			.150***	4.613	.108*	2.448			.098**	2.990	.036	.806			.118***	3.603	.067	1.512
Media Type (Text)			-.042	-1.433	-.075	-1.798			-.063*	-2.148	-.112**	-2.711			-.063*	-2.145	-.103*	-2.473
Media Type (Photo)			-.201***	-7.394	-.156***	-4.214			-.185***	-6.678	-.165***	-4.304			-.186***	-6.845	-.152***	-4.088
Media Type (A.Gif)			-.021	-1.196	-.022	-1.299			-.018	-1.000	-.018	-1.043			-.020	-1.107	-.020	-1.163
Product			.008	.399	-.015	-.514			.020	.934	-.033	-1.080			.020	.949	-.023	-.772
Price			-.037	-1.871	-.020	-.891			-.043*	-2.138	-.021	-.900			-.038	-1.891	-.016	-.729
Place			-.061*	-2.526	-.027	-.813			-.097***	-3.998	-.027	-.796			-.081**	-3.343	-.035	-1.041
Promotion			-.058*	-2.487	-.007	-.168			-.040	-1.684	-.007	-.160			-.050*	-2.103	-.004	-.099
People			.283***	14.979	.288***	10.959			.271***	14.120	.298***	10.999			.282***	14.870	.303***	11.480
Process			-.004	-.192	-.058	-1.860			-.028	-1.367	-.101**	-3.136			-.013	-.666	-.071*	-2.263
Physical Evidence			-.054**	-2.813	-.039	-1.453			-.058**	-2.958	-.043	-1.546			-.051**	-2.658	-.035	-1.305
Brand Mentioned			.088***	4.189	.039	1.339			.130***	6.076	.076*	2.541			.116***	5.502	.068*	2.317
Message Intent			.018	.975	.027	.997			.037	1.923	.025	.918			.026	1.400	.030	1.133

Variables	DV: Popularity Step 1		DV: Popularity Step 2		DV: Popularity Step 3		DV: Virality Step 1		DV: Virality Step 2		DV: Virality Step 3		DV: Engagement Step 1		DV: Engagement Step 2		DV: Engagement Step 3	
	Beta	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*
(Request)																		
Message Intent (Sentiment)			-.087***	-4.503	-.072*	-2.100			-.106***	-5.428	-.080*	-2.289			-.098***	-5.048	-.076*	-2.200
Message Intent (Question)			-.008	-.426	-.019	-.697			.018	.915	.001	.019			.005	.287	-.011	-.413
Message Intent (Announcement)			-.008	-.396	-.066*	-2.554			.007	.356	-.079**	-2.978			.002	.118	-.074**	-2.837
Day (Mon)			.144***	5.334	.107**	3.069			.163***	5.849	.124**	3.426			.155***	5.712	.118**	3.358
Day (Tue)			.045	1.787	.043	1.308			.055*	2.146	.068*	2.014			.049*	1.970	.053	1.600
Day (Wed)			.094***	3.532	.113**	3.354			.100***	3.683	.120**	3.455			.099***	3.732	.115**	3.376
Day (Thu)			.031	1.182	.055	1.604			.051	1.927	.063	1.791			.050	1.938	.067	1.964
Day (Fri)			.182***	6.287	.086*	2.211			.178***	5.974	.092*	2.291			.183***	6.310	.090*	2.302
Day (Sat)			.004	.165	-.069*	-2.093			.027	1.070	-.035	-1.021			.018	.728	-.052	-1.595
E-Marketplace (ACom)			-.073**	-2.640	.005	.050			-.025	-.882	.027	.299			-.047	-1.676	.027	.300
ACom X Tweet Length					-.193*	-2.343					-.256**	-3.050					-.220**	-2.667
ACom X Hashtags					.256***	6.117					.280***	6.554					.265***	6.308
Acom X Mentions					.044*	2.369					.015	.814					.022	1.157
ACom X Having URL					-.237***	-5.258					-.174***	-3.816					-.210***	-4.669
ACom X Media Type (Photo)					-.031	-.578					.025	.447					-.006	-.103
ACom X Product					.045	1.341					.086*	2.519					.072*	2.143
ACom X Price					-.052*	-2.561					-.062**	-2.980					-.059**	-2.919
ACom X Place					-.056	-1.912					-.084**	-2.788					-.061*	-2.067

Variables	DV: Popularity Step 1		DV: Popularity Step 2		DV: Popularity Step 3		DV: Virality Step 1		DV: Virality Step 2		DV: Virality Step 3		DV: Engagement Step 1		DV: Engagement Step 2		DV: Engagement Step 3	
	Beta	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*
ACom X Promotion					-.085	-1.846					-.068	-1.463					-.082	-1.776
ACom X People					-.031	-1.023					-.063*	-2.035					-.056	-1.856
ACom X Process					.054	1.742					.078*	2.487					.059	1.906
ACom X Physical Evidence					-.018	-.563					-.016	-.485					-.021	-.650
ACom X Brand Mentioned					.098*	2.060					.074	1.527					.077	1.603
ACom X Message Intent (Request)					-.016	-.584					.010	.348					-.011	-.408
ACom X Message Intent (Sentiment)					-.030	-.669					-.034	-.751					-.033	-.729
ACom X Message Intent (Question)					.012	.403					.019	.614					.016	.552
ACom X Message Intent (Announcement)					.080**	2.758					.124***	4.190					.112***	3.871
ACom X Day (Mon)					.047	1.203					.037	.930					.041	1.052
ACom X Day (Tue)					-.002	-.042					-.032	-.819					-.012	-.323
ACom X Day (Wed)					-.022	-.582					-.027	-.694					-.016	-.421
ACom X Day (Thu)					-.025	-.624					-.017	-.407					-.017	-.429
ACom X Day (Fri)					.128**	2.610					.097	1.919					.117*	2.384

Variables	DV: Popularity Step 1		DV: Popularity Step 2		DV: Popularity Step 3		DV: Virality Step 1		DV: Virality Step 2		DV: Virality Step 3		DV: Engagement Step 1		DV: Engagement Step 2		DV: Engagement Step 3	
	Beta	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*
ACom X Day (Sat)					.099**	2.633					.075	1.932					.094*	2.489
Adjusted R^2		.020		.336		.376		.026		.330		.370		.021		.332		.371
R^2 changes		.020***		.324***		.047***		.026***		.313***		.046***		.022***		.318***		.045***

Note. ****p* < .001, ***p* < .01, **p* < .05; Dummy variables are presented in italics (Media Type 0 = Video, E-Marketplace 0 = BCom, Day 0 = Sun); ACom X Having Media URL, ACom X Media Type (Text), and ACom X Media Type (Animated_gif) were excluded variables.

4.3 Discussion

Length Features: Unlike past research [27, 78, 145], tweet length decreases popularity, virality, and engagement. Keeping tweets short is also mentioned as one of the basic strategies [83]. Unlike past research [27, 78, 145], tweet length decreases popularity, virality, and engagement. Previous studies have suggested that longer tweets tend to enhance engagement, as they provide more detailed information and context, leading to increased retweets and likes [69, 71, 72]. Besides, longer content has been linked to stronger consumer interaction, particularly in eWOM behaviors and brand engagement [30, 42, 53]. However, the findings indicate the opposite effect, where shorter tweets drive higher engagement. This discrepancy is the evolving nature of Twitter's user behavior. With the increasing dominance of fast-paced, short-form content across social media platforms, users may prefer brief and concise tweets over lengthy ones.

Interactivity Features: Unlike past studies [43], this study finds that interactivity features (hashtags and mentions) positively affect popularity, virality, and engagement, similar to the positive influence of mentions on sharing [81]. These findings align with research suggesting that hashtags and mentions increase online engagement on Twitter [69, 76] and play a significant role in tweet diffusion and consumer interactions [53, 79]. Hashtags have been shown to improve the likelihood of receiving favorites and retweets [46, 53]. In the study of Nanath and Joy [71], hashtags and mentions decrease retweets. In the study by Alboqami, et al. [27], hashtags decrease the probability of favorites, and mentions decrease the likelihood of retweets. In the study by Han, et al. [44], hashtags and URLs do not influence engagement.

Hyperlinks increase the likelihood of favorite and retweet models [27]. Links are associated with online engagement on Twitter [69], but having URLs in this work decreases popularity, virality, and engagement. A tentative reason for the divergence from prior research is the evolving nature of social media engagement dynamics. While earlier studies suggested that hashtags and mentions might reduce interactions [71], recent trends indicate that they serve as key drivers of discoverability and conversation participation, particularly in e-marketplace settings. The context in which hashtags and mentions are used may play a role in these variations. Generic or excessive hashtag usage may deter engagement [80], whereas strategically placed hashtags relevant to trending topics can enhance tweet reach and interaction. Regarding URLs, previous research has presented mixed findings, with some studies highlighting their positive effects on engagement [27, 83], while others indicate negative impacts [12, 84]. This work also supports the mixed findings, showing that having URLs increases virality, and engagement, but reduces popularity.

Novelty Features: Although past research on the perceptions of the 7P marketing mix of Islamic banks in Indonesia reveals that the 'people' and 'product' elements were primarily utilized [52], ACom and BCom in this study focused most on 'promotion'. This aligns with findings that promotion significantly influences customer engagement in online marketplaces [9, 45, 99]. Posts containing promotions tend to generate higher interaction, particularly in e-commerce and live-streaming shopping contexts [45]. However, while past studies have linked promotional content to increased likes and comments [99], this findings suggest that promotion decreases popularity and engagement, consistent with research indicating that discount or promotional information can reduce favorites and retweets [12]. This may be due to oversaturation, where excessive promotional content leads to skepticism among users who perceive such messages as commercials.

The influences of each post topic on likes, comments, and shares are mixed [70], the same as the impacts of the 7Ps on popularity, virality, and engagement in this work. Product information decreases the probability of receiving favorites and retweets [27, 87], but it is insignificant in this work. While product information has been linked to increasing customer purchase interest and brand trust [32, 96], its role in social media engagement remains unclear. An explanation is that users may be less likely to interact with straightforward product details unless accompanied by incentives or engaging narratives [97].

The negative effect of price on virality is similar to the negative impact of retail price on advertising responsiveness [146]. Insignificant influences of price and promotion conform to the insignificance of price and promotion on marketing performance [49].

While price is a key factor in purchase decisions [89], its limited role in popularity and engagement may stem from the nature of Twitter interactions, where users might be more responsive to emotionally engaging or visually appealing content rather than straightforward price information. For process-related content, which was found to be insignificant in this study, aligns with prior findings that process is not strongly linked to achieving competitive advantage for food MSMEs [147].

The insignificant influence of product, price, and process information on popularity can be explained by the fact that brand messages containing helpful information foster retweets but not likes [97], and that the message theme or content context does not significantly affect likes and comments [87]. Price and process are not positively associated with customers' purchase intention [45]. The 'people' and 'product' categories are the most frequently discussed in consumers' perceptions of Islamic banks in Indonesia, while 'physical evidence' receives the least discussion [52]. In this study, 'people'—but not 'product'—had a positive impact on popularity, virality, and engagement, while 'physical evidence' decreased them. This supports previous findings that people play a crucial role in engagement [95], whereas physical evidence, which is more relevant in offline service contexts, may have limited relevance on SM.

In the study of Asamoah [148], none of the marketing strategies significantly influence customer purchase decisions. The insignificant influence of information (some elements of the 7Ps) could be supported by the insignificance of informational messages posted on mini-program channels regarding the role of mini-program channel use in consumers' purchase breadth in the e-marketplace [85], and the insignificant influence of informativeness on purchase intention in search engine marketing implementation [74]. This suggests that while information quality can enhance trust and decision-making [32], it may not always translate into immediate engagement on social media, where users are often drawn to content that is entertaining or visually appealing.

Consistency Features: Brand centrality increases the likelihood of a message being favorited or retweeted [27], similar to how brand mentions in this study enhance popularity, virality, and engagement. This aligns with findings that brand mentions can create a sense of inclusion for customers, fostering higher likability [37]. Users may feel more connected to a brand when it is explicitly referenced, leading to increased interactions, such as likes, comments, and retweets [30]. Besides, corporate brand names in messages significantly enhance likes and comments, especially in service industries [102], which may explain why brand mentions in this study positively influence all engagement metrics. However, past research also presents contradictory findings. While some studies indicate that brand prominence in advertisements decreases sharing behavior [101], and brand mentions in airline tweets negatively affect likes and retweets [76], this findings suggest otherwise. It could be explained by the fact that the impact of brand mentions depends on context and industry. E-commerce brand mentions could be more positively received if they provide value, such as promotions, product recommendations, or exclusive deals. Tweets with frequent organizational mentions also have been shown to receive more retweets [71], which is consistent with this findings.

Content Features: Questions are the second-ranked message intent, in line with past research indicating that asking questions is a common topic in tweets [30]. This aligns with previous findings that question-based content can increase interaction by prompting responses and engagement from users [103]. Messages with request intention insignificantly affect popularity, virality, and engagement, which is consistent with prior research showing that call-to-action tweets do not necessarily generate higher engagement compared to non-call-to-action tweets [149]. Brand messages also explicitly seeking interaction with customers have been found to have negligible effects on likes [97], suggesting that users may not respond favorably to direct requests for engagement but rather engage organically when content is perceived as valuable or relevant. The use of emotional appeals does not generate more likes and comments [102], but sentiment tweets (containing emoticons) gain propagation [81].

In this work, tweets with sentimental intent decrease popularity, virality, and engagement. The impact of sentiment on engagement in this study diverges from some prior findings. While past research indicates that sentiment-laden tweets (containing emoticons) gain propagation [81] and strong sentiment (positive or negative) enhances engagement [53], this results show that tweets with sentimental intent negatively influence popularity, virality, and engagement. Unlike airline tweets, where positive or negative sentiment drives engagement [76], e-marketplace tweets may require a more neutral or positive tone to appeal to a broad audience. The negative correlation between sentiment and engagement in this study supports research indicating that sentiment can sometimes have an adverse effect on likes, comments, and retweets [111], possibly because highly emotional messages are perceived as less informative in the e-commerce context.

Vividness Features: Past research does not support the influence of vividness on consumer brand post engagement on Twitter [43] and reveals the positive impact of photos and videos [70], indicating that richer media content generally enhances engagement. However, this work's results present a nuanced perspective. This study shows that having media URLs positively influences popularity, virality, and engagement, while media types (text and photos) negatively affect consumer interactions compared to videos. These findings align with prior studies suggesting that videos positively impact likes, shares, and retweets [12, 70, 115] and that information-rich media types (such as videos) increase forwards, comments, and likes [84]. Past research highlights that videos tend to generate more engagement than static images [42, 102], which could explain why photos in this study reduced interaction relative to videos.

On the contrary, the results diverge from some previous research demonstrating that images significantly enhance behavioral engagement on Twitter [150] and that tweets with images affect favorites and retweets [27, 76, 114]. This could be explained that while photos can improve engagement, they may not be as compelling as videos in capturing consumer attention. In addition, some studies indicate that images can negatively impact consumer engagement [79], which suggests that the effectiveness of visual media may depend on context, platform, and content type. Antoniadis, et al. [23] indicate that vividness increases a post's popularity and engagement. Images and videos have significant relationships with online engagement on Twitter [69], but not text

Timing and Frequency Features: Similar to past research indicating that posting on working days increases a post's engagement and popularity [23], tweeting on Monday, Wednesday, and Friday improves popularity, virality, and engagement, while posting on Tuesday enhances both virality and engagement. This aligns with findings that the day of the week plays a significant role in Twitter engagement [15, 69] and that workdays influence citizens' engagement [117]. Moreover, prior research suggests that social media user activities differ between weekdays and weekends, influencing engagement levels [42].

However, this study contrasts with studies suggesting that the day of the week has no significant impact on likes and comments [87] and that weekdays do not influence comments [145]. These inconsistencies could be attributed to differences in platform algorithms, audience behavior, and industry-specific factors. For example, some research indicates that while the day of the year improves likes, the day of the week decreases likes and retweets [73]. A study found that weekends attract higher brand engagement than weekdays [80], potentially because of users having more leisure time. The insignificant impact of certain days on popularity, virality, and engagement can be explained by the insignificant relationship between followers' likes and publication time (e.g., day) [116] and the insignificance of daily timing on post effectiveness [121].

5. CONCLUSION, IMPLICATIONS, LIMITATIONS, AND FUTURE RESEARCH

5.1 Conclusion

Social media is becoming increasingly essential for businesses, but best practices for e-marketplaces remain poorly understood. This study thus addresses this research gap by exploring the influences of content, media, and scheduling strategies on popularity, virality, and engagement on Twitter by examining tweets of top e-marketplaces in Thailand. Results show the negative influences of length and content features, mixed impacts of interactivity, novelty, and vividness features, and positive effects of consistency and timing features on popularity/ virality/ engagement. This study also demonstrates the moderating impact of e-marketplaces on these relationships. Most previous studies have not focused on corporate messages [46]. They also generally use human coders for content analysis, which could lead to problems such as bias, time, and inconsistency. This study employs the power of AI (GPT-4) to conduct content analysis, the same as past research regarding thematic analysis [141].

5.2 Implications for Research and Practice

For theoretical implications, this study extends the Social Media Engagement Theory by integrating three social media strategies: content, media, and scheduling, and examining their combined effects on engagement. While previous studies primarily focused on individual elements, this research proposes a holistic model for firm-generated content in e-marketplaces, highlighting how different message features interact to drive user responses. This study contributes to Social Media Communication Theory by demonstrating that message intent, brand mentions, and vividness features significantly influence online engagement, supporting the idea that effective communication strategies can shape consumer perceptions and behaviors. The findings reinforce the role of content cues in shaping engagement patterns, particularly through hashtags, mentions, and URLs. In line with Uses and Gratifications Theory, this study confirms that audience engagement is influenced by the perceived value of social media content. The positive impact of message intent, hashtags, and media URLs on engagement suggest that users actively seek specific types of content that fulfill their informational or social needs. On the contrary, the negative impact of sentiment-driven messages contradicts the traditional assumption that emotional content always enhances engagement. Furthermore, this research extends Dual Processing Theory by showing that both heuristic (e.g., media type, message intent) and systematic (e.g., tweet length, brand mentions) processing mechanisms influence engagement outcomes. This suggests that users process social media content through both quick, surface-level cues and deeper cognitive evaluations. Lastly, this study provides a theoretical foundation for understanding the moderating role of e-marketplace brands in engagement, which opens avenues for future research into how platform-specific factors shape user engagement.

For practical implications, e-marketplace tweets should be concise, ideally under 190 characters, to maximize readability and engagement. They should minimize the use of URLs, limiting them to one per tweet, as excessive links may reduce user interaction. E-marketplaces should incorporate at least two relevant hashtags per tweet and mention influencers, brands, or key users strategically to boost customer likes, retweets, and overall engagement. Besides, e-marketplaces should prioritize discussions around people and their brands, as these elements drive stronger engagement. In contrast, they should limit excessive emphasis on place, physical evidence, promotion, and price, as these factors show weaker effects on engagement. Moreover, tweets should maintain a neutral or slightly positive tone, avoiding overly emotional messaging, which may not resonate well with audiences.

Regarding media strategies, video content should be prioritized over photos and text-based posts, as videos have been shown to generate higher engagement. E-marketplaces should ensure their tweets include media URLs to enhance visibility and interaction. For scheduling strategies, e-marketplaces should post actively on Mondays, Wednesdays, and Fridays to optimize engagement while reducing posting frequency on Thursdays, which exhibit lower interaction rates. E-marketplace brands themselves (ACom or BCom) can mitigate the negative impact of long tweets, excessive URLs, and novelty features related to price, place, and people. However, they can enhance the effectiveness of interactive elements (hashtags and mentions), novelty features (unique product and process content), consistency features (brand mentions), content strategies (announcement-based messaging), and timing factors (posting on Fridays and Saturdays) to increase popularity, virality, and engagement.

5.3 Limitations of the Study and Future Research

The limitations are as follows. This study focused on two significant e-marketplaces and Twitter. While ACom and BCom are dominant players in Thailand, the findings may not fully generalize to other markets with different e-commerce dynamics. Future studies should expand to other popular e-marketplaces and social media they use. This study excluded replies and retweets to focus on the direct messages that brands use to initially communicate with customers. But customer engagement is not limited to brand-initiated tweets. Future research should explore how e-marketplaces strategically use replies and retweets to foster interactions, resolve customer inquiries, and enhance engagement. Although ChatGPT performed similarly to human coders, its responses could be biased due to the training data, and it may struggle with content that is culturally specific. Moreover, the comparison between ChatGPT and Gemini revealed inconsistencies in classifying marketing-mix elements, particularly in product, price, and people. While AI-based classification minimizes human subjectivity, discrepancies between models highlight the challenge of accurately interpreting context-dependent content. Future studies should refine prompt designs, incorporate multiple AI models for validation, and integrate human expertise to improve classification accuracy. Another limitation involves the representativeness of the sample. While this study analyzed 2,196 tweets from two major e-marketplaces over six months, which provides a longitudinal perspective, the reliance on a single Twitter scraper tool (Vicinitas) restricted the dataset to the most recent 3,200 tweets per account. This constraint may have led to the omission of older but potentially relevant data. Future research should employ alternative data collection methods, such as API-based extraction, to obtain a more comprehensive dataset. Newer versions of AI models, such as GPT-4.0, should be also used to process data further. As AI capabilities evolve, future research should assess the impact of using advanced language models for social media analytics and their ability to improve content classification.

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