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Multiple engagement by an individual on a social media post is rare: Insight from an analysis of 3.5 million Instagram user accounts and 29 user interviews

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ABSTRACT

This research examines how often and why an individual user engages with a social media post, such as reacting, sharing, commenting, or tagging, multiple times versus only once, referred to as Multiple Engagement Behavior (MEB) or Single Engagement Behavior (SEB), through two studies. The first study quantitatively analyzes 345 million interactions on 231,554 Instagram posts from 43 organizations with a combined 3,527,289 user accounts to identify the frequency of the MEB of Reacting and Commenting. Findings show that MEB occurred more than 2.1 million times, but it comprises only 0.63 % of the combined engagement, indicating that SEB is the most common. The second study qualitatively analyzes 29 social media user interviews to investigate drivers and barriers to MEB, showing that users prioritize preserving the anonymity of others and have little incentive for multiple public interactions in most situations. When they do engage in MEB, it often occurs privately, such as by direct messaging to avoid publicness. A key takeaway is that public social media post counts serve as a reasonable proxy for people counts, as platforms often withhold these people counts from the public, an impactful insight for design, legal, and marketing.

1. Introduction

Social media platforms offer users various ways to engage with content. Social media post engagement (SMPE) is *an explicit interaction by an individual with a social media post, such as liking, commenting, sharing, saving, tagging, or reacting, which indicates attention, interest, or involvement with the content*. With billions of people participating globally, SMPE on individual posts significantly shapes online relationships, spreads ideas, and influences public opinion (I. Khan, 2022). SMPE can be a single individual (i.e., a user) engaging with a specific social media post with a single interaction, such as a 'like' or 'comment' (Jansen et al., 2023), which we refer to as *Single Engagement Behavior* (SEB). A user may also engage with an individual social media post in multiple ways, such as a 'like and comment', which we refer to as *Multiple Engagement Behavior* (MEB). The relationship among these three constructs is shown in Fig. 1.

Considering the importance of SMPE, several studies have examined the characteristics of content (Dinh & Walczak, 2025), context, and creator (Jaakonmäki et al., 2017; Patton et al., 2020) as well as SEB across multiple platforms (Saleem & Iglesias, 2020; Unnava & Aravindakshan, 2021). SEB is typically measured through metrics of views, reactions (e.g., likes), comments, and shares, which businesses and content creators use to gauge success. These metrics are sometimes treated as proxies for the number of individuals who have viewed the content, assuming each interaction represents a unique user, with assumptions about the drivers of these individuals. However, the accuracy of this assumption depends on the frequency of MEB. If MEB is rare, publicly available engagement counts may be a reasonable proxy for the audience. If MEB is common, these public interaction counts would not be a reasonable proxy for audience size, leading to an overestimated

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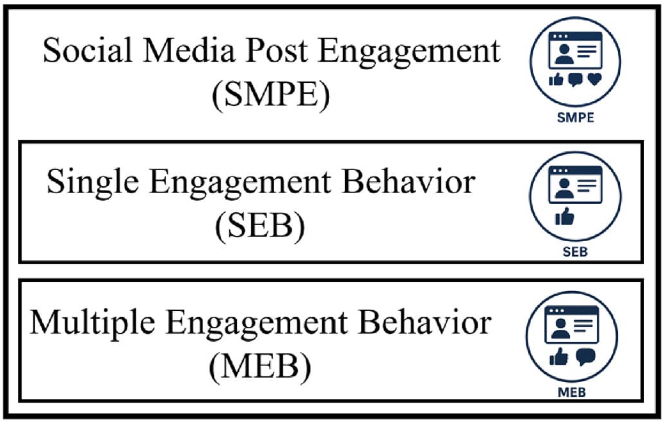


Fig. 1. Social Media Post Engagement and Two Types: Single Engagement Behavior and Multiple Engagement Behavior. SMPE refers to collectively all the interactions on a post. SEB is a single interaction on a post by one individual. MEB is two or more interactions on a post by one individual.

audience size based on a count of interactions. This overestimation can have significant consequences in legal contexts, misinterpreting interaction counts could lead to flawed estimations of individuals exposed to content. In influencer marketing, inflated interaction metrics could distort reach-based compensation models. In platform design, user experience may be optimized around incorrect assumptions of engagement depth. Finally, in economic analysis and financial projections of platform companies, accurately estimating the number of users is important for key indicators, such as customer lifetime value (Fader et al., 2005). Despite these consequences, little is known about how often users perform MEBs relative to SEBs, what types of MEBs individuals use, or why they choose to do so.

Many businesses and content creators tend to prioritize quantitative metrics, such as reactions, comments, and shares, often neglecting the depth and authenticity of these interactions (Gräve, 2019). For example, Facebook admitted to significantly overestimating video view times by counting only views over 3 s, misleading advertisers.[1] This incident highlights the risks of relying solely on quantitative metrics and emphasizes the need for accurate and holistic approaches to understanding SMPE. Focusing only on numbers without understanding the motivations and obstacles behind these numbers can overlook critical opportunities to build meaningful connections with audiences (Bazi et al., 2020; Santos et al., 2022; Yesiloglu et al., 2021). Thus, understanding the drivers and barriers of MEB is equally important as understanding its frequency. Despite SMPE widespread influence (Hudders et al., 2021), fundamental questions about MEB remain unresolved, including: *How common is MEB? What motivates an individual to engage more than once on a single social media post (or conversely, what discourages them)?*, and *Why is MEB important?* These questions form the footing for our research.

This research investigates the prevalence of MEB and explores user drivers and barriers, responding to a critical and previously underexamined gap in social media analytics. While most SMPE research focuses on content characteristics or aggregate user behaviors, little attention has been paid to how an individual engages with a single social post. This gap has implications for how we interpret social media metrics in legal contexts (e.g., determining how many individuals saw given content), marketing (e.g., assessing influencer reach), and platform design (e.g., refining engagement algorithms), among other contexts. For example, if MEB is common, then engagement metrics would not be a reliable count of people. If MEB is rare, then engagement metrics would be a reliable count of people. By investigating MEB occurrences, drivers, barriers, and implications related to SEB, this research contributes to a better understanding of the complex nature of MEB. Understanding the frequency and drivers of MEB is crucial for understanding SMPE because user decisions to interact with content are influenced by both its inherent appeal and how these actions shape users' online persona (Chung et al., 2017), allowing for selective self-presentation (a.k.a., impression management). When MEB does occur, it is important to understand the drivers behind such interactions. In doing so, this research enhances our understanding of how users navigate self-presentation, audience visibility, and privacy across social media platforms, with the focus being on single posts by an individual rather than aggregate interactions by many users. Guided by this rationale, we examine the following research questions (RQs):

- RQ1: *How frequently does multiple engagement behavior occur?*
- RQ2: *What are the (i) barriers and (ii) drivers for (a) single engagement behavior and (b) multiple engagement behavior?*

2. Literature review

SMPE encompasses a range of behaviors varying from passive consumption (e.g., reading or watching) to active contribution (e.g., sharing or commenting) (Saleem & Iglesias, 2020) on a single post. Prior research has examined numerous factors influencing these interactions (Su et al., 2025; Teepapal, 2025; Wilopo & Nuralam, 2025), such as user traits, content characteristics, and social context. One can often categorize SMPE by the *effort* (Chung et al., 2017; C. Kim & Yang, 2017; Sharma et al., 2023; J. Wang & Sundar, 2022) or *publicness* (Aldous et al., 2019) (i.e., 'the degree to which a social media action or content is visibly linked to a person's identity and observable by others') required. For example, low-effort or low-publicness (i.e., limiting exposing oneself or others online) SMPE interactions, such as pressing a like or similar reactions, are contrasted with high-effort or high-publicness SMPE interactions like writing comments or sharing posts (Carlson et al., 2019; Hinson et al., 2019; Muntinga et al., 2011; Schivinski et al., 2016; R. Sun et al., 2024; Tafesse & Wood, 2021), each SMPE carries different implications for user involvement and identification or presentation of self (or also others via actions such as tagging). Social media algorithms and psychological drivers add complexity to this landscape (Y. Choi, Kang, et al., 2023; DeVito et al., 2017; C. Kim & Yang, 2017; S. A. Kim, 2017; Y.-J. Li et al., 2025). So, understanding SMPE is a nuanced area of study, especially the interaction of effort and publicness.

The content and context of a single social media post are also factors that influence SMPE. For example, certain themes of posts tend to generate particularly higher SMPE on some platforms more than others, reflecting platform-specific user interests and norms (Aldous et al., 2019, 2023; Jiang et al., 2024). Emotionally charged content (Saleem & Iglesias, 2020) triggers strong SMPE responses, and users are more likely to react or comment when a post evokes emotions like joy, anger, or sadness. Prior work shows that a post's emotional appeal (D. Molina et al., 2021; Gerlitz & Helmond, 2013; Jung et al., 2022; Vosoughi et al., 2018), combined with the user's current emotional state (S. Li et al., 2024), can move someone from passive scrolling to active interaction (Saleem & Iglesias, 2020). Similarly, content involving parasocial relationships (Sheng et al., 2025) (e.g., posts by celebrities or influencers) or sensational, attention-grabbing elements tend to generate more SMPE, as users feel compelled to respond, provocative or personally resonant material (D. Molina et al., 2021; Gerlitz & Helmond, 2013; Jung et al., 2022; Vosoughi et al., 2018). Various theories seek to understand these observed SMPE behaviors. With the lens of communication theory (Hall, 2025), for example, these SMPE interactions fulfill various user needs. Likewise, uses-and-gratifications research (Kaur & Kathuria, 2025) suggests that people interact with social content to gratify desires for entertainment, information, social connection, or community belonging (Cheung & Lee, 2012; M. L. Khan, 2017; Zhang, 2012; Zhou et al., 2025). So, SMPE can be driven by a complex set of

[1] https://www.wsj.com/articles/facebook-overestimated-key-video-metric-for-two-years-1474586951.

drivers (Cheung & Lee, 2012; M. L. Khan, 2017; Zhang, 2012). Social media platforms, including algorithmic feeds, notification designs, and other platform features, can also add more complexity to this dynamic. These affordances shape when and how people engage with a post, while psychological drivers (e.g., the desire for social validation or reciprocity) further modulate these behaviors (Y. Choi, Kang, et al., 2023; DeVito et al., 2017; C. Kim & Yang, 2017; S. A. Kim, 2017; Y.-J. Li et al., 2025).

Beyond content characteristics and platform-specific design, social context (J. L. Hayes et al., 2020) also shapes SMPE and motivations for such engagement. Each social media platform affords distinct interaction patterns and norms (Chen et al., 2025), influencing what users do (Waterloo et al., 2018). These design differences create different *social media engagement cultures* (i.e., users may be inclined to perform certain actions on one social media platform that they would avoid on another due to differing audience expectations and technical affordances). Moreover, social media algorithms and interface cues can prompt additional engagement by exploiting social dynamics, often highlighting content that has accumulated many reactions or comments, implicitly signaling popularity or importance. Such *popularity cues* (i.e., visible indicators, such as the number of likes, shares, views, or comments, that signal how widely a piece of content has been engaged with by others, thereby influencing an individual's perception of its value, relevance, or credibility) can attract users to 'join the bandwagon', as suggested by social proof theory (Van Dalen, 2023). Research has also noted that the presence of SMPE metrics can alter user behavior (Jung et al., 2022). For example, seeing a high like count can validate one's inclination to also like that post, whereas a lack of visible engagement might suppress participation due to fear of being the first to speak up (Van Dalen, 2023).

Notably, however, much of the existing literature implicitly treats each SMPE (e.g., reaction, share, comment) as an expression of a unique user, focusing on each interaction in isolation, with a single motivation. Therefore, these SMPE metrics on posts are often used as audience size or impact proxies, assuming each countable interaction comes from a different person and a person having only a single motivation for engaging with a post. However, this assumption can be questioned because it overlooks cases where the same individual might interact with a post multiple times, potentially overestimating unique reach and ignoring multi-faceted motivations among social media users. The phenomenon of one person performing multiple actions on the same social media post at a given time (i.e., MEB) has been largely understudied, to our knowledge. These gaps in prior research underscore the need to distinguish SEB from MEB, determine the frequency of MEB occurrence, and investigate whether the motivations driving SEB are comparable to those driving MEB. Enhancing this understanding of MEB is crucial for theories of social media use (McKenna et al., 2025) and for the practical interpretation of engagement metrics (Al Montaser et al., 2025), which may not reliably indicate unique users if MEB is prevalent.

Specifically, this research investigates the frequency of MEB occurrence quantitatively through large-scale analysis of actual SMPE and then qualitatively via a user study of social media users to understand the drivers and barriers behind SEB and MEB, especially to understand the factors driving the more complex MEB on social media platforms. In doing so, we extend prior research on social media engagement to a more nuanced understanding of the ways a social media user engages and what drives engagement on a single post.

3. Conceptual framework on social media engagement

As the prior research shows, users are not only driven by content and platform affordances but also by self-reflective processes concerning how their actions will be perceived. Engaging with a social media post is a performative act (Krifka, 2024) visible (in varying degrees) to one's network and the public, so users often consider impression management (Y. Sun et al., 2021) in deciding whether and how to interact with certain social media posts. Prior studies indicate that people tend to practice selective self-presentation online, curating their activities to convey a desired image (Chung et al., 2017; C. Kim & Yang, 2017). Liking or commenting on a post can be seen as an endorsement of its message or source, so users may refrain from engaging with content that conflicts with the persona they wish to convey. For example, someone might privately appreciate a controversial post but avoid commenting or sharing it to not appear confrontational or to sidestep potential backlash. Likewise, concerns about privacy (Besmer & Richter Lipford, 2010; Bright & Logan, 2018; Farooq et al., 2023) and context collapse (Wenninger et al., 2014) can limit SMPE beyond.

Also, it is known that users often avoid actions that could expose personal information or attract unwanted attention in a public or semi-public forum (Besmer & Richter Lipford, 2010; Bright & Logan, 2018; Farooq et al., 2023). An anonymous 'like' on platforms where such interactions are not prominently displayed might feel safer to users, whereas posting a comment more conspicuously associates one's identity and opinions with the content (Aldous et al., 2019). These *social privacy calculations* might help explain why, in many cases, users stop at a single, low-effort, low-publicness SEB interaction or choose not to engage at all unless sufficiently motivated in MEB. In effect, a SEB may represent a compromise between the user's interest in the content and their management of social risks and identity, a balance extensively documented in prior work on online self-disclosure (Chu et al., 2023) and interaction etiquette (Pewnil, 2022). This backdrop of personal and social considerations sets the stage for understanding the phenomenon of MEB.

Building on this prior work, this research employs a four-level engagement framework proposed by Aldous et al. (Aldous et al., 2019), which classifies engagement by the degree of publicness. Higher levels reflect greater public association, while lower levels indicate more private interactions. Specifically, *Level-1* includes private actions like views; *Level-2* covers preferences such as reacts and saves; *Level-3* involves more public expression through comments, tags, direct message sharing, and intra-platform sharing; and *Level-4* refers to content dissemination through cross-platform sharing. On platforms like Facebook, users can react to posts in various ways (e.g., 'love', 'angry', 'sad'), but the most common reaction is the 'like' (Larsson, 2018). In this research, we use the terms 'react' and 'like' interchangeably to represent different forms of user engagement. This approach reflects the understanding that the 'like' reaction is a versatile and widely used form of interaction on social media (Ding et al., 2017).

We focus on understanding participants' drivers and barriers behind these SEB and MEB metrics, which are commonly found across major social media platforms, as presented below. Table 1 presents common SEB interactions, with definitions and example social media icons for implementation.

We note that, although there is an implementation overlap between commenting and tagging in that both require input in the comment field, tagging remains a distinct SMPE type. While comments allow users to share thoughts publicly, tagging (e.g., @username) identifies or mentions another user, sends a direct notification, and links them to the post, thereby affecting the publicness of that individual. Tagging involves alerting others, even if they are not part of the initial conversation. Therefore, we consider them separate forms of SEB due to this uniqueness.

The MEBs we investigate in this research are based on standard SMPE interactions, also commonly found across many social media platforms, derived from the SEB listed above. Table 2 presents some common MEB interactions, with definitions and example social media icons.

We selected these MEB pairs as they represent SEBs commonly found across various platforms, reserving other pairs for future research. To our knowledge, no social media platform during the time of the study provides metrics for saves, shares via DM, or cross-platform shares (e.g., Facebook to LinkedIn, LinkedIn to Reddit).

Table 1
SEB types with definitions and examples.

SEB	Definition	Example
React	refers to the explicit expression of a user's emotional response or feedback through predefined options on the platform, such as 'like,' 'love,' 'inspiring,' or 'sad,' available on the platform.	
Save	refers to the action where a user bookmarks or stores content for future reference, allowing for easy access without publicly interacting with or sharing the post.	Save
Comment	refers to a user leaving a written response or feedback directly on the content, facilitating discussion, or sharing opinions publicly.	
Share	refers to a user distributing content to their network or across platforms, amplifying its visibility and reach beyond the original audience.	Share
DM	refers to the private sharing of content between users through a platform's direct messaging (DM) system, allowing for personal communication without public visibility.	Message
Tag	refers to the act of mentioning or identifying another user in the content, creating a direct link to their profile and notifying them of their inclusion.	

Table 2
MEB types with definitions and examples.

MEB	Definition	Example
MEB01	React and save (React-Save)	Save
MEB02	React and comment (React-Comment)	
MEB03	React and share on the same platform (React-Share)	Share
MEB04	React and share to direct messages (React-Share (DM))	Message
MEB05	React and tag someone in the comments (React-Tag)	
MEB06	Comment and tag someone in the comments (Comment-Tag)	
MEB07	React and share to other platforms (React-Share (O)).	Copy link to post

4. Method

To address our research questions, we conducted two complementary studies designed to provide both breadth and depth in understanding MEB. The first study employed large-scale quantitative analysis of Instagram SMPE data to determine how frequently users engage in MEB, focusing on observable behaviors across millions of interactions, addressing RQ1. This analysis allowed us to establish baseline prevalence and provide empirical grounding for the phenomenon of MEB. However, social media platforms often restrict the visibility of certain SMPE types, preventing the measurement of many MEB combinations. Moreover, quantitative analysis alone does not reveal the underlying drivers of MEB. Therefore, the second study employed qualitative interviews of social media users to explore a broader range of SMPE and investigated the underlying motivations, social dynamics, and contextual factors influencing MEB, addressing RQ2. Together, these studies establish a cohesive research framework. Study 1 quantifies the behavioral footprint of MEB, and Study 2 interprets its psychological and social meaning. This mixed-methods approach provides a triangulation of findings, linking SMPE analysis with intent, and supporting a richer understanding of how and why MEB occurs.

4.1. Study 1: social media analytics

Data Collection. Instagram was selected as a platform to collect data, as it was one of the most popular platforms among individuals and organizations (Aldous et al., 2019; Dhanesh et al., 2022; Gruzd et al., 2018), with a diverse user base (L. Wang et al., 2020), and, importantly, it allowed, at the time of the study, identifying user accounts that engaged in MEB. Moreover, Instagram has been used in prior SMPE studies (Aldous et al., 2019; Manikonda et al., 2016), making it an excellent platform for investigating MEB.

Public data was collected from Instagram to analyze SMPE across multiple content categories. Data collection focused on publicly accessible posts, likes, and comments from a curated list of official and verified accounts representing sectors such as News, Education, Travel, and Shopping. We selected the accounts based on relevance to key thematic areas of public communication and audience interaction. Account selection prioritized official organizations, brands, and media outlets with significant follower bases to ensure the relevance and visibility of content. The data collection covered posts published between January 2012 and April 2023. Using a combination of web scraping techniques and publicly available Instagram data, we extracted post-level metadata (e.g., content IDs, captions, timestamps) as well as user-level engagement data (e.g., likes and comments).

SMPE data was collected from 231,554 posts from 43 distinct Instagram accounts for social network analysis, purposefully selected to balance feasibility and diversity, ensuring a broad digital presence. Emphasis was placed on capturing depth and representation across various categories during the selection process. While Instagram was the focus in this case, the methods used are replicable across other social media platforms, provided the necessary data is accessible, which, at the time of the study, to our knowledge, they were not.

We selected accounts from various categories to capture a broad spectrum of online interests. The categories and number of accounts were 'Education,' (n = 9, 20.9 %), 'News' (n = 5, 11.6 %), 'Travel' (n = 3, 7.0 %), 'Tourism' (n = 2, 4.7 %), 'Culture' (n = 2, 4.7 %), 'Telecommunication' (n = 2, 4.7 %) and 'Charity' (n = 2, 4.7 %). Categories of 'Sports,' 'Health,' 'Television,' 'Knowledge,' 'Shopping,' 'Equestrian,' 'Hospitality,' 'Delivery,' 'Medicine,' 'Arts,' 'Publishing,' 'Retail,' and 'Religion,' were each represented by one account (2.3 % each, 29.9 % aggregate). To mitigate potential bias from category imbalance, we normalized all engagement metrics by post count and, where appropriate, calculated per-post averages. This allowed for more meaningful comparisons across categories of different sizes. These Instagram follower counts ranged from 2025 to 15,992,308, with an average of 920,807 (SD = 2,693,876). The average number of posts for the accounts is 5,384, the minimum number of posts is 182, and the maximum is 36,627 (SD = 7951).

For each Instagram post, we considered two primary SMPE metrics: Reacts and Comments, as these are the only ones visible to users on Instagram, allowing for MEB data collection. This permitted us to investigate MEB02 (React-Comment). While Study 2 explores a broader range of MEB types, including combinations such as React-Save, React-Share, and React-Tag, Study 1 focuses specifically on MEB02 (React-Comment) due to data visibility constraints. Instagram, at the time of data collection, only provided public metrics for Likes (i.e., Reacts) and Comments, whereas other interactions such as Saves, Shares (including via DM or to other platforms), and Tags were not publicly available or programmatically accessible for large-scale analysis. Thus, MEB02 was the only reliably measurable MEB combination across millions of users. Despite this limitation, analyzing MEB02 provides valuable insight into the prevalence of MEB and sets a foundation for understanding how frequently social media users engage with the same post in more than one publicly visible way. The qualitative insights from Study 2 complement this quantitative foundation by examining a full spectrum of MEB types and offering interpretive depth into user motivations. Together, these two studies offer a triangulated perspective. Namely, the first study quantifies MEB occurrence within the limits of observable behavior, while the second study contextualizes these behaviors within users' lived experiences across interaction types. The posts in the dataset account for a total engagement of 352,579,442 interactions, with 345,740,585 (98.06 %) being Reacts and 6,838,857 (1.94 %) being Comments. On average, each post received 2141 reacts, ranging from 1 to a maximum of 236,689 Reacts. For Comments, posts averaged 50, with a minimum of 1 and a maximum of 53,720 comments.

Measures: The consolidated dataset tracked three key metrics: a unique post identifier, post headline, and originating organization. SMPE was analyzed by mapping reacts data, which tracked likes using content identifier, username, and comment data, linking content identifier to comments, capturing the text message and username. Both datasets (i.e., Reacts and Comments) were matched using content identifier, and then combined into intersection data to analyze users who both Reacted and Commented on the same post.

Data Analysis: Addressing part of RQ1, we filtered the datasets to include relevant information on Reacts and Comments, matching data using content identifier and username to identify users who performed both actions on the same post. We focused on the overlap between Reacts and Comments, reporting the number and calculating this as a percentage of total engagement, which is the total of both Reacts and Comments.

4.2. *Study 2: social media user study*

Supplementing the quantitative study, the follow-up user study employed semi-structured interviews to gather rich qualitative data on participants' drivers for engaging with social media platforms. Additionally, attitudinal data were collected through closed-ended questions. This second study captured insights from individuals actively participating in reacting, commenting, sharing, tagging, and saving, focusing on MEB.

Recruitment: We recruited participants who: (1) spent at least 1 h per day on social media, (2) used at least two social media platforms, and (3) frequently interacted with social media content. The pre-interview survey assessed participants' social media usage, with selections based on their frequency of activity and engagement through reactions, comments, shares, and saves. To capture a broad range of motivations, efforts were made to include participants from diverse age groups and genders, as internet use can be influenced by factors such as age and gender (Teo, 2001).

Inclusion/Exclusion Criteria: As part of the selection process, participants completed a pre-interview detailing their social media usage, including hours spent online and their top five most used platforms. They also rated their engagement in eight interactions, viewing, liking, commenting, sharing, sharing via direct messages, sharing via other platforms, tagging, and saving, on a frequency scale (never, rarely, sometimes, very often, always). Those who selected 'never' or 'rarely' for all interactions were excluded, and only participants who frequently engaged (choosing 'sometimes,' 'very often,' or 'always' for at least three interactions) were included.

We initiated recruitment by posting interview requests primarily on Upwork and some via LinkedIn, targeting individuals active on multiple social media platforms. The response was quick, and applicants were carefully screened based on the study's criteria. Selected candidates underwent initial interviews to ensure diversity and relevant expertise. Once confirmed, participants were briefed on the study's purpose, and interviews were scheduled via video calls.

Participants: A final sample of 29 United Kingdom (UK)-based participants was recruited through online platforms, with 27 from Upwork and 2 from LinkedIn. We chose UK-based participants to minimize cultural differences that could influence SMPE (Krishen et al., 2021), as cultural variations could significantly impact social media behavior and shape engagement tendencies within specific demographics.

Age and Gender Distribution: Participants were aged 25–29 (12 individuals), followed by the 17–24 group (7 participants, 24.1 %). The 30–34 and 40+ age groups had four participants each (13.8 % each), while the 35–39 group had the least representation with two participants (6.9 %) (see Table 3). The gender distribution was fairly balanced, with a slight male predominance, i.e., 16 males (55.2 %) and 13 females (44.8.%) (see Table 3).

Frequency of Social Media Use: All 29 participants are frequent social media users, averaging about 4 h of daily use, consistent with their classification as frequent users. Both the mode and median were 4 h, highlighting the regularity of this usage. Social media engagement time ranged from 1 to 10 h, showing varying intensity among participants (see Table 3).

Fig. 2 shows the distribution of participants' first and second most used social media platforms. Instagram was the most used, with 65.5 % of participants (19 out of 29) identifying it as their primary platform, followed by Facebook at 13.8 % (n = 4) and TikTok and LinkedIn, each at 10.3 % (n = 3). For the second platform, our participants are using Facebook (27.6 %), Instagram (24.1 %), YouTube (17.2 %), Twitter (13.8 %), TikTok (10.3 %), and Snapchat (6.9 %). The 29 participants were asked to answer all the engagement questions, thinking of their most used social media platform, and they also described the overall similarities and differences of their interaction with the second most used platform.

Interview Protocol: To explore the drivers behind different types of SMPE behavior on social media, we developed a semi-structured interview protocol. We designed the interview questions in four parts. A full list of interview questions is available in Appendix A. In the first part, participants were asked about their SEB motives for the eight individual SMPE interactions separately (DeVito et al., 2017; S. A. Kim, 2017), focusing on their most-used social media platforms (Aldous et al., 2019). For example, they were prompted with, "You usually add a comment on a post because …," addressing RQ2. In the second part, we explored motives for MEB by asking, "When you come across a post, how do you typically interact with it?" We examined six combinations of reacting (e.g., liking) with other interactions (e.g., commenting, sharing, tagging) to address RQ2. Participants also reported the frequency of these combinations, such as, "After liking a post, how often do you add a comment?" to address RQ1. In the third part, we explored the barriers to SEB for the eight interactions by asking participants to complete statements like, "You usually choose not to click to share on the post because …", addressing RQ2. In the fourth part, participants were asked to compare their engagement patterns with those of their second most used platform. The question, "Think of your next most-used social media platform. Do you engage in the same way on this other platform? What is the same? What is different? Please specify the platform name," aimed to uncover participants' awareness of audience differences across platforms and highlight engagement motives (Aldous et al., 2019).

Interview Procedure: All interviews were conducted remotely via digital platforms (i.e., Teams or Zoom) and lasted 45–60 min. With participants' consent, sessions were held in English and audio-recorded.

Table 3
Participants' demographics, the top 1st (platform-1) and 2nd (platform-2) most used platforms, and the number of hours they spend on social media at the time of interviews. IG – Instagram, FB – Facebook, YT – YouTube, TW – Twitter, TT – TikTok, LI – LinkedIn, SC – Snapchat.

ID	Gender	Age	Hours	Platform (Pl.) 1	Pl. 2	ID	Gender	Age	Hours	Pl. 1	Pl. 2
P1	F	22	4	IG	SC	P16	M	20	5	IG	SC
P2	M	37	4	IG	FB	P17	M	19	3	IG	TT
P3	F	26	2	IG	FB	P18	F	33	4	IG	YT
P4	M	28	4	FB	IG	P19	F	31	10	LI	FB
P5	M	29	6	IG	FB	P20	M	18	3	IG	TT
P6	M	29	4	IG	FB	P21	F	27	6	IG	TW
P7	F	26	4	IG	YT	P22	M	26	8	IG	FB
P8	M	33	4	IG	TW	P23	F	44	2	IG	YT
P9	F	23	5	TT	IG	P24	M	26	6	IG	YT
P10	M	37	2	FB	IG	P25	M	51	1	LI	IG
P11	F	30	8	FB	TW	P26	M	45	1.5	LI	IG
P12	F	19	1.5	IG	TT	P27	F	43	1.5	FB	TW
P13	F	28	2	IG	YT	P28	F	27	4	IG	FB
P14	M	28	2	TT	IG	P29	M	26	5	IG	FB
P15	M	17	3	TT	IG						

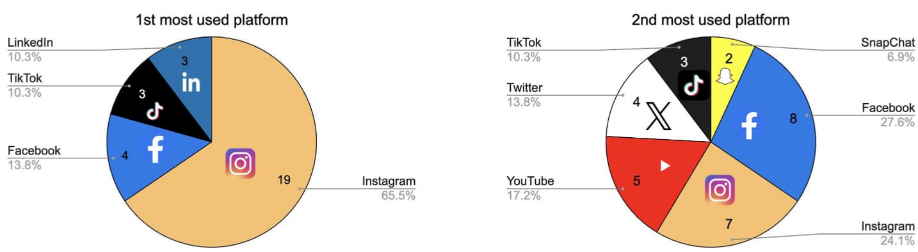


Fig. 2. The distribution of the participants' first and second most used social media platforms.

To encourage openness, confidentiality was assured, with all data anonymized for research use only. Compensation, modeled after Upwork's pay structure, averaged $15, exceeding the UK minimum wage of £11.81, reflecting the value of participants' contributions.

Measures: The pre-interview examined participants' behaviors on their most used social media platforms. Using a Likert scale from 'never' to 'always,' participants reported how frequently they engaged in SEBs. This structured approach gave a comprehensive view of user SMPE patterns. Our study used a four-part interview protocol to explore (a) SEB drivers, (b) MEB drivers, (c) barriers to SMPE, and (d) cross-platform SMPE patterns.

SEB Drivers: We examined the individual drivers and barriers behind eight specific SEBs commonly provided by social media platforms: React, Save, Comment, Share, DM, and Tag. These responses address RQ1.

MEB Drivers: This section explored the drivers and barriers behind six MEBs: MEB01(React-Save), MEB02 (React-Comment), MEB03 (React-Share), MEB04 (React-Share (DM)), MEB05 (React-Tag), MEB06 (Comment-Tag), and MEB07 (React-Share (O)). Additionally, the frequency of these repeated interactions was analyzed to assess habitual patterns. These findings primarily offer insights into RQ1.

Barriers to SEB and MEB: To explore reasons for not interacting with social media posts, participants were asked why they chose not to engage using the eight SEB interactions. These responses aimed to provide insights into RQ2.

Cross-Platform SEB and MEB: Participants were asked to compare their engagement behaviors on their top two most used platforms. These responses provided insights into platform-specific nuances, helping to address RQ2.

Data Analysis: We applied a weighted mean to analyze Likert scale data, assigning different weights to responses based on perceived importance. The process involved (1) assigning weights to each response, (2) calculating weighted values by multiplying each response's weight by its frequency, and (3) deriving the weighted mean by summing the values and dividing by the number of respondents. This method offers flexibility and emphasizes significant responses.

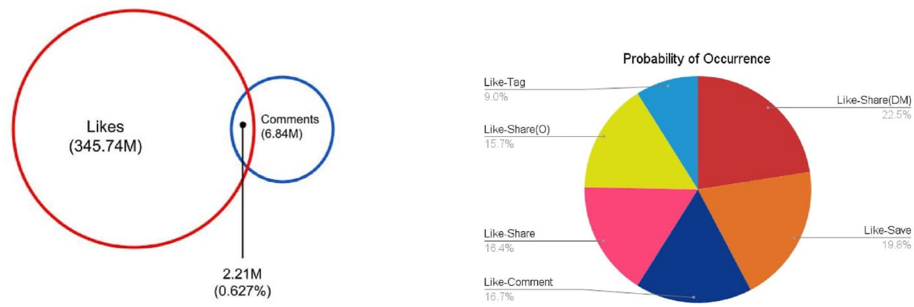
The interview recordings were transcribed verbatim and analyzed using phenomenological analysis (Hycner, 1985), followed by grouping. A researcher uninvolved in the interviews reviewed the transcripts, identifying key dialogue units (Robinson, 1949) that reflected participants' experiences and interpretations of their SMPE. Phenomenological analysis requires "bracketing the researcher's meanings and entering into the world of the individual being interviewed" (Hycner, 1985, p. 281). These units were then grouped, reduced, and thematically coded to identify recurring patterns. Through iterative discussions, the research team reached a consensus on key findings, providing insights into the motivations behind SMPE.

5. Study 1 results

For RQ1 (How frequently does multiple engagement behavior occur?), we conducted an extensive study on reactions and comments to analyze SEB and MEB on Instagram. The key finding was the overlap between users who reacted to a post and those who commented on it (MEB02 (React-Comment)). Specifically, 2,211,156 MEB02 occurred, which is a lot of interactions; however, this accounted for approximately 0.63 % of total engagement. Fig. 3a shows the Venn diagram of reacts and comments overlap (MEB02 (React-Comment)).

The quantitative analysis showed there were 345,740,585 reacts and 6,838,857 comments, with 2,211,156 MEB02 (React-Comment), representing 0.627 % of Instagram engagements (352,579,442 engagements; reacts plus comments). Although this percentage is low, the vast number of interactions on platforms like Instagram suggests a significant number of users actively engaging in MEB. This insight is critical when analyzing social media data, as the data is limited by the visibility of engagement metrics, as platforms often restrict access to detailed interaction data.

We also split the data by account category (e.g., News, Shopping, Education) to examine how MEB02 varied across content categories. Table 4 shows the quantitative analysis of user engagement metrics across account categories. There are differences in the frequency of



(a) (b)

Fig. 3. The MEBs from Study 1 (a) and Study 2 (b). In (a), the Venn diagram of the Reacts (345,740,585) and Comments (6,838,857) with MEB02 (React-Comment) being 2,211,156 (0.627 % of total accounts) based on data from Study 1, and in (b), the probability of MEB occurrence based on interview data from Study 2.

Table 4
Descriptive statistics of SEB and MEB across content categories. Likes and Comments represent total counts; MEB2 (React and Comment) refers to instances where the same user both liked and commented on a post. Ordered by number of MEB02 occurrences.

Category	Likes	% Likes	Comments	% Comments	MEB02 (React -Comment	% MEB02	# Posts	% Posts
News	68,935,143	19.94	3,048,908	44.58	656,232	29.68	57,765	24.95
Telecom	2,401,204	0.69	457,376	6.69	214,121	9.68	12,647	5.46
Travel	29,761,864	8.61	487,171	7.12	191,034	8.64	4186	1.81
Culture	5,713,286	1.65	291,295	4.26	144,416	6.53	15,684	6.77
Shopping	650,577	0.19	123,354	1.80	111,548	5.04	5570	2.41
Television	5,567,879	1.61	337,495	4.94	104,784	4.74	33,002	14.25
Education	3,687,323	1.07	97,770	1.43	42,247	1.91	18,700	8.08
Charity	2,197,408	0.64	33,886	0.50	21,624	0.98	21,350	9.22
Hospitality	583,270	0.17	20,964	0.31	14,087	0.64	3588	1.55
Knowledge	282,238	0.08	7376	0.11	3969	0.18	1463	0.63
Arts	134,492	0.04	2969	0.04	2172	0.10	2491	1.08
Delivery	94,831	0.03	18,158	0.27	1497	0.07	1069	0.46
Publishing	28,003	0.01	972	0.01	535	0.02	1312	0.57
Others	225,703,067	65.28	1,911,075	27.94	702,890	31.79	52,727	22.77
ALL	345,740,585		6,838,769		2,211,156		231,554	

MEB02 (React-Comment) across content categories. While the overall intersection rate was 0.627 %, categories such as Shopping and Telecommunication exhibited significantly higher proportions of MEB02, with 16.84 % and 8.10 % respectively. These categories also recorded a high average number of MEB02 per post, 20.03 and 16.93 for Shopping and Telecommunication, respectively. In contrast, high-engagement categories such as News and Travel showed much lower MEB02 percentages (0.92 % and 0.64 %), with high average likes (1193.37 and 7109.86) and comments (52.78 and 116.38). Table 5 shows the quantitative analysis of user engagement metrics across account categories normalized by the number of posts per category.

Table 5
Descriptive statistics of SEB and MEB across content categories. Metrics are normalized by the number of posts per category: L/post (Likes per post), C/post (Comments per post), MEB02/post (MEB02 instances per post). % MEB02 indicates the proportion of unique MEB instances relative to the union of like and comment users.

Category	# Posts	L/post	C/post	MEB02/post	% MEB02
Travel	4186	7109.86	116.38	45.64	0.64
Shopping	5570	116.80	22.15	20.03	16.84
Telecom	12,647	189.86	36.16	16.93	8.10
Others	52,727	4280.60	36.24	13.33	0.31
News	57,765	1193.37	52.78	11.36	0.92
Culture	15,684	364.27	18.57	9.21	2.46
Hospitality	3588	162.56	5.84	3.93	2.39
Television	33,002	168.71	10.23	3.18	1.81
Knowledge	1463	192.92	5.04	2.71	1.39
Education	18,700	197.18	5.23	2.26	1.13
Delivery	1069	88.71	16.99	1.40	1.34
Charity	21,350	102.92	1.59	1.01	0.98
Arts	2491	53.99	1.19	0.87	1.61
Publishing	1312	21.34	0.74	0.41	1.88
ALL	**231,554**	**1493.13**	**29.53**	**9.55**	**0.63**

These differences in SMPE show that it is not just about how users engage, but how they choose to do so—whether by liking, commenting (i.e., SEB), or both (i.e., MEB). This lack of insights makes understanding the motivations behind MEB crucial. It highlights the importance of directly interviewing social media users about their engagement patterns across different interaction combinations on posts and individual posts, as we did in Study 2.

We investigate whether MEB occurrence varies by content characteristics through a category-level analysis. As shown in Table 5, the frequency of MEB02 (React-Comment) varies substantially across organizational account categories. For instance, Shopping and Telecommunication posts yielded higher MEB02/post rates (20.03 and 16.93, respectively), while categories like News and Travel, despite higher total engagement, had much lower MEB02 percentages (0.92 % and 0.64 %). These variations suggest that the context and thematic focus of a post influence the likelihood of multiple engagements. This finding provides empirical grounding that supports the qualitative insights to be presented from Study 2, where participants reported content-specific motivations (e.g., utility, fun, or personal relevance) as drivers for MEB. Thus, our category-based findings align with and reinforce Study 2's conclusions regarding content-related drivers of MEB.

6. Study 2 results

6.1. RQ1: How frequently does multiple engagement behavior occur?

Fig. 3b above showcases the varying probabilities of repeat engagement combinations on a given platform based on participant responses from Study 2. The highest probability is 22.53 % for MEB04 (React-Share (DM)), followed by MEB01(React-Save) at 19.75 %, MEB02 (React-Comment) at 16.67 %, MEB03 (React-Share) at 16.36 %, MEB07 (React-Share (O)) at 15.74 %, and MEB05 (React-Tag) at 8.95 %.

6.2. *RQ2: What are the (i) barriers and (ii) drivers for (a) single engagement behavior and (b) multiple engagement behavior?*

We first looked at what barriers and drivers influence people to interact with a social media post or not as foundational before exploring both SEB and MEB. To illustrate our qualitative analysis results, Table 6 connects actions on social media sites with the themes that emerged from the qualitative analysis, which we explain below in detail.

To provide a holistic view of what motivates or inhibits single and multiple engagement behaviors, we created Fig. 4, which combines both drivers and barriers identified in Study 2. Fig. 4 compares the frequency of each theme's occurrence across SEB and MEB. While Family & Friends and Utility emerged as dominant motivators across both engagement types, other themes, such as Fun & Happiness and Content Seeking, were stronger drivers of MEB. Conversely, barriers such as Bleak Content and Fame & Ads were more often cited as reasons for avoiding SEB, while Privacy & Publicness and Audience Sensitivity (coded under "Family & Friends) were commonly referenced deterrents for MEB. This integrated view illustrates the nuanced decision-making behind SMPE and highlights the dual role some themes play, either encouraging or suppressing user action depending on context and visibility.

Content Seeking. Prior research differentiates between mindless scrolling (Baughan et al., 2022) and mindful engagement (Purohit & Holzer, 2021). In our interviews, users were prompted to pause and interact with content driven by personal interest, with sports, hobbies, and DIY projects being the most frequently mentioned social media post types that encouraged engagement. Some quotes from this theme are: "*I think [posts I share] can be something about art or but now […] I like books or dogs*" (Participant-28); "*Because me and my husband were very big foodies […] we [interact with] a recipe*" (P-1); and "*I follow [and] like lots of sports-related posts; so maybe I would also stop for those*" (P-19). Sports were previously identified as strong storytelling (Laurell & Söderman, 2018) and marketing (Witkemper et al., 2012) subjects on social media platforms. Here, we include content about the gym, yoga, exercise, and adjacent forms of healthy living.

Similarly, the effect of social media on hobbies and DIY culture is documented (see (Deibert, 2014; Hargreaves & Hartley, 2016), among others). Our research revisits the importance of "how-to" and "walk-through" content in the *Utility* theme. Here, we include content about small entrepreneurship and self-development. Apart from pausing to view the content in detail, users mentioned Reacting, Sharing, and DMing the content.

Bleak Content. In our interviews, users mentioned that they frequently avoid sad or depressing posts by scrolling past them and would rarely (if ever) like them. Some examples are: "*If it's something very negative, let's say, like someone fighting or someone hating on someone I just don't want to see that because it would make me sad*" (P-11); "*usually when it's fun, not when it's something depressing, I would probably share it*" (P-12); and "*I'm originally [Redacted], so I'm reading something very sad about the situation there […] I would keep scrolling because I don't wanna read that at the moment*" (P-19). Common mentions of this issue came from the immigrant and expatriate interviewees about the news pieces on their countries or regions. Although these types of social networks allow these users to maintain a link to their home countries, they might also become outlets of stress and depression for displaced international communities (Yu et al., 2019).

Fame and Ads. Fame influenced participants' decisions to like or not like content. While brands were often associated with Reacts, personal celebrities prompted hesitation due to concerns about influencer marketing and content blended with ads. Prior research cites the concept of social media influencer capital (Freberg et al., 2011), where social capital (positive or negative) is shaped by interacting with famous figures online. In our study, participants were either subconsciously or overtly aware of these dynamics. Some examples from this theme are: "*the advertised stuff when that comes through, I just, I completely skip through*" (P-16); "*I always check [the celebrities] and view them and see*

Table 6
Interactions associated with conceptual themes emerging from the qualitative analysis.

Action vs Theme	Content Seeking	Bleak Content	Fame & Ads	Family & Friends	Fun & Happiness	Design & Suitability	Relatedness & Controversy	Utility
View	✓ (7)			✓ (2)		✓ (3)	✓ (2)	
Like	✓ (6)		✓ (2)	✓ (7)			✓ (3)	
Save					✓ (6)	✓ (4)		✓ (26)
Comment				✓ (11)			✓ (10)	
Share	✓ (5)				✓ (1)		✓ (6)	
Share (DM)	✓ (2)			✓ (10)	✓ (2)			
Tag				✓ (13)				✓ (3)
Share (O)				✓ (10)				✓ (2)
Not Share (O)								✓ (2)
Not View		✓ (7)	✓ (5)	✓ (2)		✓ (3)		
Not Like		✓ (5)	✓ (2)	✓ (2)				
Not Save								
Not Comment				✓ (5)			✓ (5)	✓ (2)
Not Share				✓ (6)				
Not Share (DM)				✓ (3)				
Not Tag								
MEB01 Like-Save	✓ (1)				✓ (1)			✓ (3)
MEB02 Like-Comment				✓ (5)				✓ (4)
MEB03 Like-Share	✓ (1)							✓ (5)
MEB04 Like-Share (DM)				✓ (3)	✓ (1)			
MEB05 Like-Tag				✓ (1)	✓ (2)			
MEB06 Comment-Tag					✓ (2)			✓ (1)
MEB07 Like-Share (O)				✓ (1)				✓ (1)

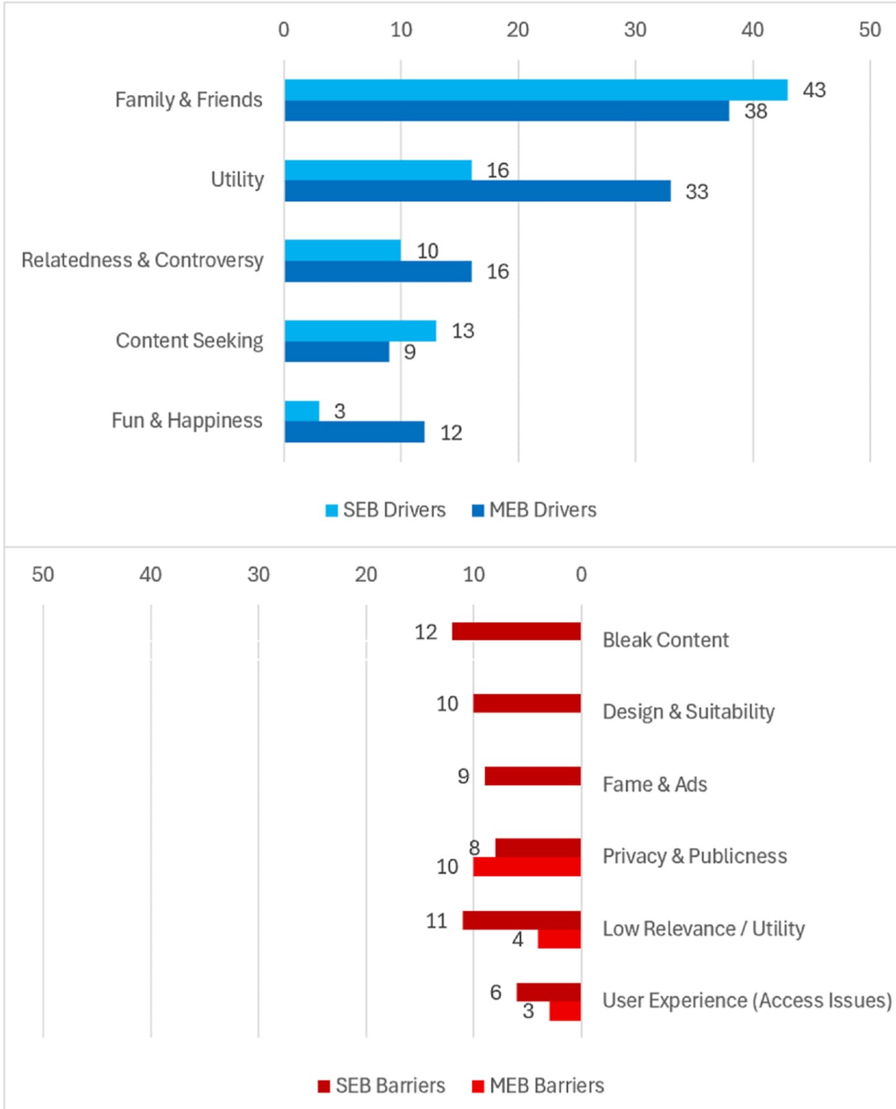


Fig. 4. Comparison of Motivational Drivers for SEB and MEB based on Thematic Analysis from Study 2 User Interviews.

what the comments are being posted by the users […] go to the comments section and see how people are commenting on that post–that's it" (P-15); and "*I would rarely press the like button on those for like if I follow any celebrities*" (P-19).

Family and Friends. As the most mentioned theme in the interviews, the presence of friends and family members influences all forms of decisions around SEBs (or lack thereof). Several subthemes emerge under this category, explicated in the following paragraphs.

Support. Interacting with friends and family posts on social media is seen as a form of support and camaraderie. Liking or commenting on such a post is regularly quoted as a "show of love" or a "boost" ("*my friends or family I'll comment cause I know them and I just wanna tell them that they look beautiful or that their pictures […] like to boost their ego, I guess*," P-8). This is especially true if a family member or a friend has a business, is a creator (e.g., an artist who shares their work, a gardener who shares their flowers, etc.), a student who shares academic achievements, and so on. Previous research (Chambers, 2013; Williams & Merten, 2011) supports that SEBs can sustain family bonds and create intimacies. Our participants mentioned that they reserve some interactions on social media only for the people they know. As much as family and friends were cited as a reason for interaction, someone not being in that closed circle of acquaintances was also a reason for not interacting with their content.

Self-disclosure Toward the Different Types of Family Members or Friends. Comparing the first and second most used platforms of the participants, the types of family members or friends were also an indicator for interaction, non-interaction, and the types of content shared or interacted with on social media.

First especially, Facebook was mentioned many times as a social network where the "older" members of the family were present ("*The people that I have on my Instagram versus the people that I have on my Facebook account: the people I have on my Instagram accounts are all like young, however, on Facebook, it's [more] the older generation of people*," P-19). Participants were keenly aware that they had separate audiences on different platforms with Instagram and TikTok being younger, Facebook being older, and LinkedIn being more professional. Accordingly, they were sensitive toward the content that they shared or interacted with on each platform according to their audience there ("*I think some people can just become like bothered by it […] I'm also scared […] like the stuff I read, like [I] share is cringe like not funny*" P-8).

Second, users were aware of the social nuance between close versus distanced friends and family members and weighed their interactions with them through the lens of self-disclosing their interest in what these individuals share ("*maybe we were all at university together or we work* *together and perhaps now we're not as close […] they might find it strange that I'm commenting*" P-9). Users might feel more free to interact with or to self-disclose the things that they want concerning a post made by a close friend or family member ("*If it's someone who's close that I wanna comment on, nothing will limit it [but if it is someone I am not close to] generally people would be like afraid […] of how other people would react [to their comments] and they would prefer not to.*" P-19).

Participants noted that they would React, Share, or Comment on certain types of content on one platform but avoid doing so on another, depending on the presence of specific groups of friends or family members on each platform.

User Experience. It was frequently mentioned that the cross-access of the content of some platforms was easier than others ("I've had a situation like that […] someone sent me a link and I'm about to open it, *and it's asking me to register […] so I'm not sending,*" P-4). This impacts interaction behavior, particularly across generations. Some participants noted that platforms like Instagram were avoided by parents, making it difficult to share Instagram content with them.

Social Capital and Reciprocity. Social capital is closely linked to social media use (Gil de Zúñiga et al., 2012), and our interviews revealed that participants were strategic in selecting and sharing content. They carefully considered the density and context of the content before posting it on social media ("*it doesn't mean that I share every post with my friends because nobody has much time to see every message of yours,*" P-15). This issue is particularly relevant in friend circles, where sharing excessive, unrelated, or low-quality content can result in a loss of social capital. Participants also aimed to maintain reciprocity on social media: if friends or family frequently interacted with their posts, they felt obliged to reciprocate. Conversely, if someone did not engage with their content, participants were less likely to engage with that person's posts ("*if I for example already shared a few posts before and this person did not answer them, didn't reply and I'm like, OK, I'll probably would stop*" P-19). This aligns with previous research, which identifies reciprocity as a key driver of social media engagement (Lewis, 2015; Luo et al., 2011; Oh & Syn, 2015).

Fun and Happiness. Funny content emerged as a recurring theme in nearly all interviews. Participants often saved content that made them laugh and shared it either publicly or via DMs. This content type also drove MEBs of MEB01 (React-Save) or MEB04 (React-Share (DM)). Users identified funny content that made them smile or laugh, saved it for future revisits, and then shared it with others. Previous studies explore these types of shares under the concept of social capital (Fu et al., 2017; Julien, 2015). Participants who share funny content are motivated by a desire to cheer others up or share something they felt "needed to be seen." Some examples are: "*if I see […] a funny post and I […] tag [my brother] in it for a bit of fun*" (P-7); "*I want to show [a post] to my friends that are not on Instagram, then I would definitely save that funny video for my friend*" (P-3); and "*We can laugh together if it's funny […] because I want to make them happy.*" (P-14).

Design and Suitability. Content suitability for online social networks was a key factor in whether participants chose to view it. Many reported scrolling past content they deemed inappropriate for their circle. Beyond platform rules, perceptions of appropriateness vary across communities (Alper, 2013; Hu et al., 2014; Jain et al., 2014). Interestingly, post design—such as visuals and fonts—was not a strong driver of interaction. Only a few participants mentioned saving visuals or designs they liked.

Utility. A key reason for Share (O) and MEB07 (React-Share (O)) with a post was its utility to the user. Posts featuring motivational content, tips and tricks, business advice, how-tos, recipes, guides (e.g., top movies or travel spots), and life hacks were all identified as having strong utility value. Some examples are: "*there's like videos that show you like gym tips, how to do certain moves at the gym and that'll be useful*" (P-19); "*some useful information […] for me, it's really often if I pick some travel video and maybe I see some video of a new cafe in the city […] maybe we can go to this cafe on weekends to get some coffee*" (P-11); and "*[I share] life hack […] DIY or building stuff or travel destinations*" (P-19). Users noted they would save a post or tag someone who might benefit from the information. Joint actions like MEB03 (React-Share), MEB01(React-Save), and MEB06 (Comment-Tag) are commonly driven by such posts. In our interviews, the utility was also the primary reason for Sharing (O) content between platforms, particularly to share with friends and family who are active on one platform but not the other.

Frequency of Single Interaction. The single interaction responses were measured on a 5-point scale: 'always,' 'very often,' 'sometimes,' 'rarely,' and 'never.' To derive insights, we used a weighted mean, assigning weights from 0 to 4, where 'never' was given a weight of 0 and 'always' a weight of 4. Fig. 5 illustrates the probability of occurrence for each interaction type. 'View' was the most frequent, with a weighted mean of 3.2 and a 15.1 % probability. 'React' followed closely with a weighted mean of 3.1, corresponding to a 14.5 % probability. Sharing via DM ranked next with a weighted mean of 2.8 and a 13.0 % likelihood, slightly ahead of 'Share,' which had a weighted mean of 2.7 and a 12.8 % probability.

Sharing through other social media applications ('Share (O)') and the 'Save' function both recorded a weighted mean of 2.6, with a 12.4 % probability of occurrence. Interestingly, 'Comment' and 'Tag' interactions also shared an identical weighted mean of 2.1, each with a 9.9 % probability. This symmetry highlights a balanced tendency among users to both Comment on posts and Tag others.

Barriers to SMPE. Participants chose not to interact with social media content for several reasons. They often avoided content that was sad or emotionally heavy, preferring to scroll past rather than engage. Fame-related posts, especially those involving personal celebrities, were met with hesitation due to concerns about influencer marketing and perceived advertising. Interaction was also influenced by social proximity—users were less likely to engage with content from individuals outside their close circle of friends and family. Platform-specific dynamics further shaped behavior, as participants adjusted their engagement based on who was present in their network on each platform. Additionally, user experience barriers, such as difficult access to content or required logins, discouraged interaction. Finally, content that was seen as inappropriate or lacking personal relevance was often ignored.

Addressing RQ2 (*What are the (i) barriers and (ii) drivers for (a) single engagement behavior and (b) multiple engagement behavior?*), the last five rows of Table 6 above show the motivations that prompt users to engage in MEB in social media.

Content Seeking. Users who actively seek content often exhibit combined actions like MEB03 (React-Share) and MEB01 (React-Save). This suggests that when a post is valuable or aligns with personal interests, users not only engage with it but also share it with others, emphasizing its perceived importance ("*it's something […] I want other people to see*" P-4) or bookmark it for future reference ("*if I save it, I know that I'm gonna use it for later*" P-24).

Family & Friends. Content related to family and friends frequently elicits combined interactions of MEB02 (React-Comment) or MEB04 (React-Share(DM)). Especially when family members and friends share personal experiences like birthdays, parties, celebrations, and vacations, it becomes almost like a duty to acknowledge these events ("*Those [birthday, vacations, celebrations, etc.] videos as well […] I always comment on people like family and friends*" P-6).

Fun and Happiness. Engaging content that exudes elements of joy, humor, or entertainment often encourages users to MEB01 (React-Save), MEB04 (React-Share (DM)), MEB05 (React-Tag), and MEB06 (Comment-Tag). ("*If it's a funny video, I'm going to like it then in comments I'm going to tag them [friends] all*" P-3). Such content holds the potential for revisiting, whether for personal enjoyment or sharing in different contexts.

Utility. Posts seen as practical or beneficial often result in repeated interactions, such as MEB02 (React-Comment), MEB03 (React-Share), and MEB06 (Comment-Tag). This suggests that users not only value utility-driven content but are also inclined to discuss, share, or direct it

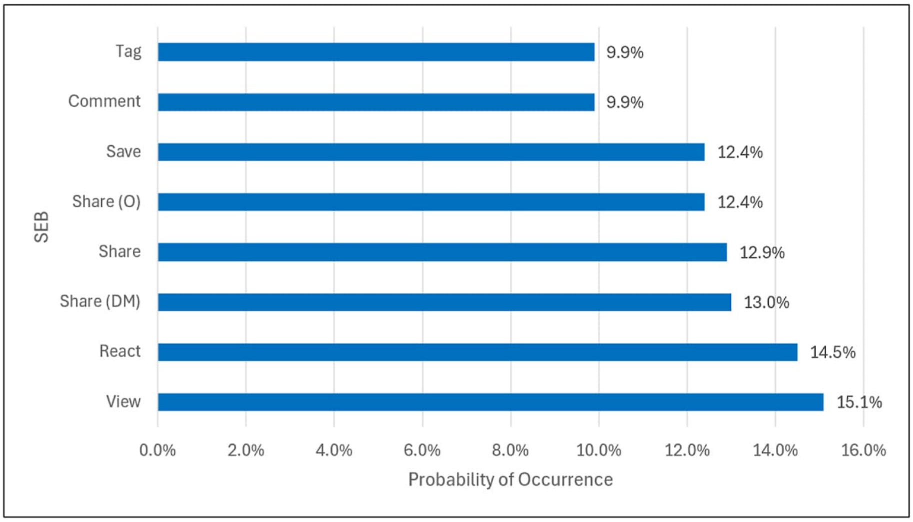


Fig. 5. The probability of occurrence of SEB on participants' first most used social media platform. The most frequent interaction is 'View' with a probability of 15.1 %, followed closely by 'React' at 14.5 %. The least frequent interactions are 'Tag' and 'Comment' with a probability of 9.9 %.

to others, highlighting its perceived importance. This behavior is more frequent when the content aligns with users' everyday interactions with others ("*[somebody] may have asked me earlier in the day about the best running sneakers […] if I see a post about describing a very good sneakers that can be used for running, I'll send it to them immediately" P-6*).

6.3. Quantitative distribution of user engagement motives

Table 6 above presents the frequency of each driver and barrier resulting from content analysis of user interactions across various engagement types. A frequency analysis of user engagement motives revealed the following distribution: **Family and Friends** was the most frequently observed motive with **81 coded instances**, followed by **Utility** (n = 49), **Relatedness and Controversy** (n = 26), and **Content Seeking** (n = 22). Motives with lower frequencies included **Fun and Happiness** (n = 15), **Bleak Content** (n = 12), **Design and Suitability** (n = 10), and **Fame and Ads** (n = 9). These counts reflect the relative prevalence of each motivational category across all coded engagement behaviors.

6.4. Study 2 user study summary

The qualitative component of this research in Study 2 was designed to complement the quantitative findings of Study 1 by exploring the motivations and contextual factors driving MEB, providing depth that purely behavioral analytics cannot capture. The interview findings align with established engagement principles and extend prior work by highlighting overlooked dimensions of SMPE user decision-making, particularly concerning privacy concerns, audience sensitivity, and the strategic use of SMPE behaviors across platforms. For example, the qualitative findings contribute to identifying selective SMPE behaviors shaped by social and contextual factors. As discussed, while prior research has examined SMPE as a function of content type and emotional response, our study reveals that users often regulate their interactions based on audience visibility, self-presentation goals, and concerns about overexposure. This distinction is particularly relevant in the case of MEB, where users weigh the benefits of repeated SMPE against the potential risks of drawing attention to themselves or the content they interact with. Thus, the qualitative findings contribute a novel understanding of how individuals consciously regulate their SMPE interactions based on interpersonal and platform-specific considerations.

7. Discussion

Understanding MEB has significant implications for both theoretical and applied perspectives in social media research. With the infrequency of MEB, simple interaction counts (e.g., Reacts, Shares, Comments) serve as a reliable proxy for audience reach. For broad content performance evaluations, focusing on SEB counts is sufficient. The rarity of MEB emphasizes its potential as a high-engagement signal, suggesting that when users engage multiple times with a social media post, they demonstrate a deeper connection to the content compared to SEB with a post.

Frequency of MEB: The quantitative and qualitative data confirm that MEB is rare, a percentage, with users seldom engaging in repeated forms of interaction simultaneously, opening lines of possible new research in this area concerning why MEB occurs so infrequently. Users might perceive performing two or more actions on the same post as redundant or unnecessarily effortful, especially if the added value of the second action is low and the effort or publicness is high. There may also be an unspoken norm of 'not over-engaging' with a single social media post to avoid cluttering others' feeds or appearing too fixated. As a result, many of the motivations that drive SEB (e.g., curiosity, mild interest, momentary emotion) may not escalate to MEB unless amplified by some factor. To date, the literature has not explicitly addressed these inhibiting factors, as MEB has not been recognized as a distinct phenomenon. This is an area for future research with this study providing nascent insights examining when and why users break the one-engagement-per-post convention. The next step is to draw on user engagement theories and contextual factors, from platform affordances to psychological drivers, to determine whether the motivations for MEB are an extension of those for SEB or if they represent qualitatively different triggers.

Certain MEB combinations, like MEB04 (React-Share (DM)) and MEB01 (React-Save), are more common, indicating a trend where some users engage more deeply with content. The diversity in MEB patterns reveals users' varied preferences for engaging with content (Aldous et al., 2019). A notable tendency is the shift toward private or personal engagement, with actions like MEB01 (React-Save) and MEB04 (React-Share (DM)) becoming more common. This suggests users are selective about publicly endorsing content, likely driven by privacy concerns (Bartol et al., 2023; Bibhu et al., 2021; Quinn & Epstein, 2018), fear of social media algorithm backlash (DeVito et al., 2017), or a preference for intimate, one-on-one sharing (Ma et al., 2016). Following (Beckett, 2010), we assert that SMPE includes both exposure and interactive behaviors, with MEB representing a deeper connection with content than SEB.

Online Relationships as Drivers of SEBs: One of this study's central findings is the strong influence of family and friends on online SMPE, showing how offline relationships shape digital engagement beyond algorithms and marketing strategies. Privacy concerns, publicness, disclosing information about others, often deter public interaction. Users engage most with social media content that aligns with their interests, such as hobbies, and favor instructional materials like DIY videos, emphasizing social media's educational role (Utz & Wolfers, 2022). Emotional regulation also plays a part, as users seek positive content and avoid negativity, reflecting social media's mental health impact (Braghieri et al., 2022; Wongkoblap et al., 2017). Skepticism toward influencer marketing is evident, with users distinguishing between branded and personal celebrity content. The study highlights a preference for utility-driven, relevant content over aesthetics. Publicness concerns and limited motivation for MEB suggest a need for content offering actionable value while protecting user privacy (Aldous et al., 2019; Atiq et al., 2022; Gil de Zúñiga et al., 2012).

Drivers of MEB: Our analysis shows utility-focused content (e.g., guides, how-tos, recipes, life hacks) drives most MEB, followed by humorous and topic-specific content. Users frequently React, Share, Save, or DM these posts. Study 2 reveals platform-specific behaviors: MEB04 (React-Share (DM)), while MEB02 (React-Comment) occurs mainly among friends and family. Humorous content often prompts Tagging, enhancing social connectivity. Utility content, in particular, triggers a broad range of SMPE, underscoring its strong influence on user engagement. The tendency to share utility posts across platforms, MEB07 (React-Share (O)), highlights the importance of shareability for broader audience reach. Marketers and brands should account for cross-platform sharing behaviors, while platform developers could enhance sharing features or partnerships. Engagement motives are similar across platforms, but engagement volumes vary, showing that while content may have universal appeal, SMPE interaction patterns differ by platform (Aldous et al., 2019).

When an individual does perform MEB, it may signal a strong or multifaceted motivation. Intuitively, an individual is more likely to engage multiple times if a post resonates on multiple levels or fulfills several needs that one action alone cannot satisfy. For instance, a social media post by a close friend, an individual might React to express an emotional response and Comment to show public support and encouragement; this Reaction fulfills an instant emotional impulse, and the Comment serves a communicative and relational purpose. Such scenarios suggest that MEB occurs when content is highly salient to the user (due to personal relevance, strong emotion, or interpersonal connection) and triggers more than one kind of engagement intent. Indeed, topics (Chung et al., 2017; Sannon et al., 2019) tied closely to personal identity or values, for example, posts about one's health, political stance, or social causes, tend to evoke stronger reactions and could prompt selective MEBs from those deeply invested (Chung et al., 2017; Sannon et al., 2019). Likewise, interpersonal factors (A. Choi, D'Ignazio, et al., 2023; Sharma et al., 2023) can drive MEBs: if the post comes from someone the individual cares about (e.g., a family member or friend), the person may go beyond a perfunctory, low effort, low publicness React and also Comment or Share to amplify their support (J. L. Hayes et al., 2020), even though these SMPE interactions are higher effort and higher publicness. In essence, the motivations behind SEB and MEB might overlap (both stem from interest and emotional response), but MEB likely requires an extra impetus, namely a convergence of motivations that makes an individual increase their engagement. So, motivations between SEBs and MEBs most likely diverge. This aligns with the idea that MEB on one social media post reflects a deeper level of SMPE (Alexander & Azer, 2023; D. Y. Kim & Kim, 2021) than a SEB. In other words, MEB can be seen as an indicator that the post has struck a chord strong enough to compel multiple expressions from the same individual.

A comparison across social media platforms also raises important considerations. While Instagram served as the focal point of Study 1 due to data accessibility, Study 2 revealed that SMPE behaviors often differ across platforms. For instance, participants described Facebook as more formal or family-oriented, influencing their hesitation to publicly interact with certain content, while Instagram and TikTok were viewed as more expressive or youth-oriented, fostering bolder interaction patterns. These variations suggest that platform affordances and audience expectations significantly mediate both SEB and MEB. Our use of UK-based participants limits cross-cultural insights; however, given that social media behaviors are known to vary based on cultural norms (Jackson & Wang, 2013), around self-presentation, privacy (Farooq et al., 2024), and collectivism versus individualism, future studies should examine MEB patterns across diverse cultural contexts. For example, Tagging behavior and DMing may be more common in cultures emphasizing social harmony and discretion. Expanding this line of research to include participants from different regions would strengthen the generalizability of the findings and offer richer insights into how social and cultural factors shape MEB.

7.1. Theoretical implications

Both studies support the finding that MEB is relatively rare as a percentage (i.e., less than one percent in our dataset of hundreds of millions); however, if the number of social media interactions is large, the absolute number can be substantial. However, in individual accounts, explicit SEB counts are likely a reasonable proxy for the number of users interacting with posts. Surprisingly, this key finding has not been widely explored in prior literature, to our knowledge, even though understanding the number of people interacting with social media content is crucial for understanding social media user behavior. From a theoretical standpoint, MEB challenges the conventional assumption that each interaction represents a unique user. This assumption underpins many models of online engagement, marketing reach, and legal interpretations of audience size. However, our findings reveal that interaction counts are largely reliable proxies for unique users; but, the presence of MEB introduces a caveat in cases with extremely large audience sizes. However, for accounts with small audiences, both the percentage and absolute number of MEB users will likely be small.

MEB provides distinct insights into social media behaviors beyond passive or single interactions. Unlike SEB, which may reflect low-effort engagement, MEB might indicate heightened interest, stronger innate psychological need, social signaling, or strategic content amplification (R. A. Hayes et al., 2016; Ronzhyn et al., 2023; Vaast et al., 2017). Recognizing this distinction with MEB allows platforms, marketers, and content creators to better interpret engagement trends. For example, if a post generates a disproportionately high MEB rate relative to its SEB, it may signal a particularly resonant or controversial topic, warranting further analysis. Additionally, MEB patterns can inform platform design decisions, such as refining engagement metrics or providing users with more explicit interaction options that align with their motivations. These are all exciting areas for future research and system design.

MEB can further be understood through the lens of social media affordances, especially the needs-affordances-features (NAF) perspective (Vaast et al., 2017). NAF suggests that engagements are outcomes of individual-driven psychological needs that are fulfilled by the affordances – users' actions through technology, enabled through the features of a social media application. As discussed above, more than one engagement (see section 3) is a precursor of a strong emotional response (motivation) mediated through social media affordances, enabling interaction and activity. Thus, social media users exhibiting MEB may be driven by stronger innate psychological needs, engaging with social media posts through multiple affordances.

7.2. Practical implications

Additionally, understanding MEB offers several specific practical insights. First, given the low occurrence of MEB, interaction counts are a reliable proxy for the number of people engaging with content, especially since platforms often hide this data. Second, users appreciate a personalized engagement experience, fulfilling psychological needs (Vaast et al., 2017). Recognizing distinct patterns allows platforms to tailor features to user preferences, creating affordances that address user's needs. For example, if many users favor Saving compared to Sharing, enhancing bookmarking or saving options could improve usability and satisfaction.

Another notable finding is the low usage of both React-Tag features together (MEB05), suggesting that certain combinations may be unintuitive or perhaps unsupported by current interface designs. Platforms could explore interface cues or interaction shortcuts that encourage meaningful combined MEBs—such as enabling seamless transitions from Reacting to Tagging or suggesting Tagging when a user Reacts to content that is commonly Shared within close social circles. Additionally, frequent private Sharing mechanisms (e.g., MEB04 React-Share (DM)) suggest a preference for controlled, intimate communication over public interaction, again returning to concerns of publicness. Social media platforms should consider enhancing DMing features with personalization options (e.g., quick-send to frequently messaged contacts) or ephemeral sharing modes that offer users more privacy control. These features will create social media affordances necessary to fulfill social media users' needs (Vaast et al., 2017).

React-Saving behavior (MEB01) also emerged as a dominant form of MEB. Platforms could better support this by allowing saved content to be organized into folders, annotated, or shared selectively, thereby increasing utility and engagement longevity. Similarly, for marketers and content creators, emphasizing shareable, evergreen, and utility-driven content—such as how-tos, guides, or curated lists—can increase both SEB and MEB across public and private channels. These findings also highlight an opportunity for social media analytics systems to introduce a composite "deep engagement" metric that tracks MEB patterns, helping advertisers and content strategists identify content that prompts both users' attention and actions. Finally, platforms might consider designing engagement dashboards that differentiate between SEB and MEB, enabling users and businesses to understand not only how many interactions occurred but also how intensively individuals engaged with content.

To translate our findings into platform design recommendations, we suggest several feature-level interventions. First, platforms should consider surfacing "related actions" prompts—for example, nudging users who Save a post to also Share it via DM, or offering contextual Tag suggestions after a Comment is made. Second, UI elements could be reorganized to group high-frequency MEB pairs (e.g., React-Save, React-Share(DM)) in proximity, minimizing friction in performing repeated actions. Third, platforms should enable users to track and revisit their own engagement history—such as displaying recently Saved or Shared content with Tagging options, thus reinforcing interaction loops. Fourth, enhancing private interaction channels (e.g., DMs) with lightweight feedback mechanisms like emoji reactions or save confirmations could encourage richer SMPE without requiring public interaction. Finally, analytics tools provided to creators and businesses should distinguish between SEB and MEB to highlight not just reach but depth of engagement, allowing for more informed content strategies tailored to user behavior.

7.3. Limitations, strengths, and future work

To address concerns regarding representativeness, future research should expand the sample in several keyways. First, while our Instagram dataset included a diverse set of 43 organizational accounts, it did not examine individual user types (e.g., influencers, everyday users) whose engagement patterns may differ significantly. Including these user types could help uncover whether MEB is more prevalent in personal versus institutional contexts. Second, our qualitative sample consisted solely of UK-based participants, which limits the cultural scope of our findings. Prior research suggests that privacy norms, social media habits, and motivations for engagement vary across cultural and national contexts. Future work should purposefully sample across multiple countries and cultural groups to assess how MEB behaviors generalize across socio-cultural settings. Also, web analytics data collection is not always flawless (Jansen, 2006), so there may be technical factors cloaking some of the MEB taking place, although we have no indication this is so.

Additionally, while our study examined a broad range of SEB and MEB types, it did not include combinations involving content creation (e.g., reposting with commentary) or platform-specific features such as Stories, Reels, or algorithmic suggestions. These may reveal deeper or more nuanced SMPE behaviors for both SEB and MEB. Future research could also investigate how MEB evolves over time, using longitudinal tracking with analysis (Jansen et al., 1998; Jiang et al., 2024) to capture changes in user behavior as platforms introduce new features or as social norms shift. Finally, experimental methods could complement observational (Jiang et al., 2022) and interview data to test causal mechanisms, such as whether interface changes directly affect the likelihood of MEB. Expanding this work to more platforms and longitudinal contexts would provide a more complete picture of how and why users engage multiple times with the same content.

Finally, while our findings offer actionable insights, it is important to contextualize their practical significance within the variability of individual user behavior. Social engagement on digital platforms is shaped by personal preferences, relational dynamics, and contextual factors that vary among individuals and cultures. Therefore, while SMPE counts may serve as a broad proxy for audience reach, the nuances of MEB are not uniformly applicable across all audiences. Recognizing this, our study does not offer universally prescriptive rules; however our research does highlight SMPE patterns that can inform more adaptive, personalized system design in the social media domain, By designing systems that are sensitive to variation in SMPE depth, privacy preferences, and interpersonal context, platforms can better support users' needs and offer more meaningful measures of content performance. This is an area for future research.

Despite these limitations, our findings offer an important initial step in quantifying and contextualizing MEB. Our mixed-method approach of quantitative and interview data strengthens the findings by aligning reported and actual behaviors. The findings provide a foundation for future research to build upon, particularly by testing MEB prevalence in different digital environments and refining methodological approaches to ensure broader applicability.

8. Conclusion

This research comprehensively examines MEB, revealing its rarity but highlighting its theoretical and practical significance. Through large-scale quantitative analysis and qualitative interviews, we establish that while MEB accounts for a small fraction of interactions, it represents a distinct and meaningful form of engagement influenced by content relevance, social relationships, and strategic self-presentation. Our findings support assumptions about social media metrics as direct proxies for audience reach. Then, by examining the motivations and constraints shaping MEB, this research contributes to a more refined understanding of social media engagement on individual posts and offers implications for platform design, marketing strategies, and audience analytics. Future work should expand this inquiry across diverse social media ecosystems and cultures to further validate and contextualize MEB behaviors.

CRediT authorship contribution statement

Kholoud Khalil Aldous: Writing – original draft, Methodology, Investigation, Formal analysis. **Sercan Şengün:** Writing – original draft. **Joni Salminen:** Writing – original draft, Conceptualization. **Ali Farooq:**

Writing – original draft. **Soon-Gyo Jung:** Conceptualization. **Bernard J. Jansen:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT 4o to copy-edit and address the blank screen problem. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

A APPENDIX. Interview questions

Table 7 shows the list of questions asked during the interview.

Table 7
The list of interview questions

#	Question
Q1	I am going to ask you some questions about certain actions that you often perform on social media platforms. Think of your topmost used social media platform, and answer: You usually view a post because… (note: not just scrolling through but stopping and viewing) You usually click like or other reactions on a post because … You usually save a post because … You usually add a comment on a post because … You usually share a post because … You usually share a post via direct message on the same platform because … You usually share a post via other social media applications because … You usually tag someone on a post because …
Q2	At times, we may perform more than one action, such as liking and commenting, commenting and sharing, liking and saving, or other combinations of these actions, on social media platforms. When you come across a post, how do you typically interact with a post? After liking or other reaction to a post, describe a situation where you would also Comment on the post… After Liking a post, how often do you add a comment to the same social media content? [scale: never, rarely, sometimes, very often, always] After liking or other reaction to a post, describe a situation where you would also Save the post… After Liking a post, how often do you Save the same social media content? [scale: never, rarely, sometimes, very often, always] After liking or other reaction to a post, describe a situation where you would also Share the post… After Liking a post, how often do you Share the same social media content publicly? [scale: never, rarely, sometimes, very often, always] After liking or other reaction to a post, describe a situation where you would also Share the post via DM… After Liking a post, how often do you Share the same social media content privately through a private message? [scale: never, rarely, sometimes, very often, always] After liking or other reaction to a post, describe a situation where you would also Share the post via other social media applications… After Liking a post, how often do you Share the content on other social media applications? [scale: never, rarely, sometimes, very often, always] After liking or other reaction to a post, describe a situation where you would also Tag someone… After Liking a post, how often do you Tag someone on the same social media content? [scale: never, rarely, sometimes, very often, always]
Q3	At times, we perform do not interact, such as no viewing, no liking, no commenting, no sharing, no saving, or other actions, with a post on social media platforms. Let's talk about these situations now. When do you usually choose not to view a post: … (note: not just scrolling through but stopping and viewing) You usually choose not to click Like the post because … You usually choose not to add a Comment on the post because … You usually choose not to click to Save on the post because … You usually choose not to click to Share on the post because … You usually choose not to Share the post via direct message on the same platform because … You usually choose not to Share the post via other social media applications because … You usually choose not to Tag someone on a post because …
Q4	Think of your next most used social media platform. Do you do the same engagement behavior on this other platform? What is the same? What is different? Please specify the platform name.

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