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The impact of influencers on brand social network growth: Insights from new product launch events on Twitter

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ABSTRACT

In the ever-evolving marketing landscape, influencers play a pivotal role in shaping brand perception and expanding social network followings. This study, grounded in Social Network Theory, examines the impact of influencers on brand social network growth during new product launch events. Leveraging an extensive dataset of over two million tweets from Twitter (now X), we empirically analyse three video game releases to uncover the characteristics and behaviours of influencers within their networks that drive follower migration to the sponsored brand's social network. Our findings highlight the importance of frequent influencer-follower interactions in enhancing brand awareness and directing followers to brand social networks. Furthermore, influencers who occupy central social hub positions and exhibit high popularity are particularly effective in fostering brand growth. This research provides practical guidance within the realm of influencer marketing, offering several valuable insights for both companies and influencers.

1. Introduction

The rapid advancement of digital technologies and the widespread adoption of social media platforms have transformed how consumers interact with information, brands, and products. This evolution has brought significant shifts in consumer behaviour and decision-making processes, influencing every stage of the consumer journey (Kannan & Li, 2017; Lamberton & Stephen, 2016; Filieri et al., 2023a).

Amidst this change, social media influencers have emerged as central figures, exerting considerable influence over consumer perceptions due to their ability to disseminate information and opinions about brands and products (Kim & Kim, 2021). These digital creators are increasingly recognized as brand ambassadors (Pei & Mayzlin, 2022), playing a pivotal role in social media marketing strategies (Appel et al., 2020; Beheshti et al., 2023). The Influencer Marketing Benchmark Report[1] reveals that the influencer marketing industry is projected to reach approximately $21.1 billion in 2023. Over 75 % of brands now allocate dedicated budgets to influencer marketing, with many planning further increases.

Despite the growing interest from both practitioners and researchers (Sánchez-Fernández & Jiménez-Castillo, 2021), a deeper understanding of the interactions among influencers, users, and brands is still needed (Vrontis et al., 2021; Taillon et al., 2020; Belanche et al., 2021). Additionally, there is a dearth of studies utilizing real-world secondary data from social media necessary for a comprehensive understanding of this dynamic (Ye et al., 2021; Syrdal et al., 2023; Sheth & Kellstadt, 2021). Finally, while communication during product launches has been acknowledged as crucial for campaign success (Baum et al., 2019), the role of influencers in this context remains underexplored.

Our study aims to address these gaps by investigating how influencers contribute to brand social network growth during product launches, leveraging Twitter (now X) data. Grounded in the principles of Social Network (SN) theory (Borgatti & Halgin, 2011; Granovetter, 1973; Gulati, 1998; Granovetter, 1983), we examine the behaviours and characteristics of influencers that encourage followers to migrate to the brand's social network. In our study, influencer behaviour is conceptualized as the suite of actions executed by influencers within their social networks that facilitate connectivity with other users. In contrast, influencer characteristics pertain to the distinctive attributes that influencers cultivate within their interpersonal dynamics across the network. For this study, we employ a quantitative approach, utilizing real data from Twitter, now rebranded as X, relating to the release of

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[1] https://influencermarketinghub.com/influencer-marketing-benchmark-report/#toc-2.

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three new video games. Gaming is a highly social environment with strong network effects, where users often look at each other – and at social media – for cues on which games to try (Tudón, 2022; Tian et al., 2024).

This study identifies three critical factors driving brand social network growth: frequent interactions between influencers and followers, the influencer's central position as a social hub within the network, and the popularity of influencer posts. While prior research has acknowledged the significance of network position and relational ties in facilitating information diffusion (Liu et al., 2017; Wang & Chiang, 2009), our findings advance this understanding by revealing that frequent interactions and the popularity of influencer posts play a pivotal role not only in reinforcing connections between users and influencers but also in more effectively driving the followers toward the brand, surpassing the impact of content. Moreover, our results indicate that influencers positioned as social hubs within the network exhibit a significantly greater capacity to attract followers to the brand, effectively expanding their reach. Specifically, the social hub position appears to be more effective in driving brand growth compared to a social bridge position. This centrality not only enhances the visibility of the information they share but also encourages the creation of content that resonates closely with audience preferences, thereby solidifying their influence (Wang et al., 2022).

This study makes substantial contributions on both theoretical and practical fronts. Theoretically, this study advances the field of influencer marketing and SN research by exploring the characteristics and behaviours of influencers within their social networks that are crucial for driving the expansion of brand social networks. While previous research has often emphasized individual traits of influencers (Litterio et al., 2017), this study highlights the broader context of network interactions and behaviours, offering a more holistic perspective. By employing empirical data from Twitter (now X), this research moves beyond traditional approaches, providing objective insights into influencers' effectiveness during new product launches. Lastly, our analysis is situated within the context of a new product launch, where the influencer's role is naturally pivotal and can significantly shape campaign and product outcomes (Baum et al., 2019). Practically, these findings offer actionable guidance for companies aiming to identify and collaborate with influencers who can drive brand growth through effective behaviours and characteristics. Moreover, they provide influencers with strategies to enhance their impact by optimizing their network roles and interactions, thereby ensuring measurable contributions to the brand.

2. Literature overview

The literature on influencers has grown significantly, with increasing attention to their characteristics and selection criteria (Litterio et al., 2017; Masuda et al., 2022), the traits they manifest (Cheung et al., 2022; Casaló et al., 2020), and their impact on user engagement, purchase intention, and brand trust and attitude (Jun & Yi, 2020; Sánchez-Fernández & Jiménez-Castillo, 2021; Leek et al., 2019).

Influencers are widely perceived as opinion leaders who can shape the attitudes and behaviours of their audiences (Freberg et al., 2011). They may be domain experts or individuals with extensive social networks, known as social connectors. When influencers are recognized as opinion leaders by their peers, their ability to influence becomes even more pronounced (Casaló et al., 2020). Influencers exhibit distinct features, such as respected opinions, proactive community involvement, frequent contributions to the community, and a perceived sense of taste within their communities (Leal et al., 2014).

Unlike traditional celebrities, influencers often cultivate deeper and broader relationships with their followers, enhancing their credibility (Djafarova & Rushworth, 2017; Schouten et al., 2019). According to Ohanian's (1990) source credibility theory, the effectiveness of endorsements hinges on the perceived credibility of the endorser, evaluated through trustworthiness, expertise, and alignment with the endorsed product (Kapitan & Silvera, 2016; Ooi et al., 2023). Trustworthiness reflects perceived integrity and honesty (Goldsmith et al., 2000; Ohanian, 1990), while expertise denotes the endorser's skills or authority in a specific domain (Yuan & Lou, 2020; Ohanian, 1990). Influencers leverage their credibility to foster positive attitudes and behaviours toward sponsored products (Jin & Muqaddam, 2019; Jiménez-Castillo & Sánchez-Fernández, 2019; Goldsmith et al., 2000).

Authenticity has also emerged as a key influencer attribute (Koles, et al., 2024), with frameworks developed to guide influencers in managing authenticity (Audrezet et al., 2020). Authenticity enhances message receptivity and purchase intentions (Labrecque et al., 2011; Moulard et al., 2016; Moulard et al., 2021; Napoli et al., 2014). Frequent interactions between influencers and followers further boost perceptions of authenticity, fostering trust and favourable brand attitudes (Dwivedi & McDonald, 2018; Jun & Yi, 2020; Ooi et al., 2023). Such interactions suggest intrinsic motivation, enhancing influencers' perceived engagement with their audiences (Jun & Yi, 2020).

Furthermore, the attractiveness and popularity of influencers significantly affect the perceived effectiveness of their endorsements (Delbaere et al., 2021; Torres et al., 2019). Ki and Kim (2019) found that influencers who post attractive content are perceived as opinion leaders, consequently increasing consumers' desire to emulate them. Similarly, (Gupta et al., 2020) observed that popular and attractive influencers are often viewed as more trustworthy.

Finally, the type of content shared by influencers – whether informative or entertaining – and its quality emerge as essential factors that significantly enhance consumers' propensity to follow influencer recommendations, thereby exerting a substantial influence on their purchase decisions (Lou & Yuan, 2019; Filieri et al., 2023a). These elements not only foster stronger engagement but also build greater trust in the brand, further amplifying the persuasive power of influencers (Ki & Kim, 2019; Lou & Yuan, 2019).

Research methodologies in this field vary widely. Some studies focus on theoretical advancements, delving into conceptual frameworks and proposing novel theoretical models to elucidate various aspects of influencer-brand dynamics (Campbell & Farrell,2020). Others adopt empirical methodologies like surveys and experiments to assess consumer responses to influencer marketing (Filieri et al., 2023b; Lou & Yuan, 2019; Fink et al., 2020; De Veirman et al., 2017; Borges-Tiago, et al., 2023). An emerging trend involves leveraging real data from social media platforms, with a growing number of studies tapping into actual user behaviour on these platforms (Casaló et al., 2020; Leek et al., 2019; Syrdal et al., 2023; Argyris et al., 2020). This data-driven approach offers a more concrete and tangible perspective, bridging the gap between theory and practical applications in influencer marketing. However, challenges in accessing and analysing this data continue to limit its broader adoption (Sheth & Kellstadt, 2021; Sheth, 2021).

The existing literature enhances a common understanding of various aspects related to influencers (Vrontis et al., 2021). However, despite the wealth of research in this domain, three significant gaps persist necessitating further investigation. First, most research focuses on individual influencers' traits, neglecting the broader context of their network interactions and the impact on brand social network expansion (Litterio et al., 2017). Moreover, the scarcity of studies using real-world social media data highlights a critical need for further exploration (Ye et al., 2021; Syrdal et al., 2023). Finally, there is limited understanding of influencers' role during new product launches, where their impact on campaign and product success is crucial (Baum et al., 2019). Grounded in the SN theory, this study addresses these gaps by identifying the key characteristics and behaviours of influencers that contribute to brand network growth during product launches, using real-world Twitter data.

3. Theoretical background

3.1. Social network theory

In online social networks, users play a central role in driving interactions and shaping the flow of information (Litterio et al., 2017). These platforms enable users to establish connections based on shared interests, preferences, and affiliations, forming a web of relationships that facilitates communication and content dissemination. This creates a dynamic system where information spreads rapidly across the network (Litterio et al., 2017).

Opinion leaders are pivotal figures within online social networks, exerting considerable influence on the behaviour and decisions of other users (Zhang et al., 2018). These individuals accumulate large followings and serve as key nodes in the network. Due to their prominence, the content they share is frequently amplified through reposts and shares, further extending their reach and impact (Araujo et al., 2017). The frequent reposting and sharing of content from opinion leaders exemplifies a network-driven dynamic, as they become trendsetters who actively shape the flow of information. Their influence extends beyond immediate connections, flowing through the broader network and indirectly shaping the behaviours and preferences of users further distanced from the source (Goldenberg et al., 2009).

To better analyse these influential actors and their role in shaping the network, researchers employ SN theory. This theory enables the study of relationships between actors within a network, offering insights into how information propagates and how social structures are formed (Borgatti & Halgin, 2011; Granovetter, 1973; Borgatti & Ofem, 2010). These relationships are conceptualized as networks (Goldenberg et al., 2009). Social networks are represented as a collection of nodes – such as individuals, organizations, or groups – connected by various social ties, including friendships, shared memberships, or financial transactions (Laumann et al., 1978; Nelson, 1989). By examining these ties, SN theory elucidates the structure of relationships and reveals how the position of an actor within this structure can influence his/her actions and those of others (Granovetter, 1983). This approach is crucial for understanding the dynamics of network growth, both at the individual and aggregate levels (Goldenberg et al., 2009).

The increasing popularity of SN theory across disciplines stems from its ability to focus on both individual actors and the relationships connecting them (Borgatti et al., 2009; Zhang et al., 2018). Rather than isolating individual behaviours, SN theory emphasizes the broader social context of interconnected actors, which collectively shapes economic and social actions (Tichy et al., 1979; Wasserman, 1994; Gulati 1998). Within this theory, the positioning of individuals within the network, the strength and quality of their connections, and the nature of the content they share emerge as essential determinants of information propagation and behavioural evolution, thereby shaping the flow of influence throughout the network (Tichy et al., 1979; Granovetter, 1973; Wang et al., 2022). These factors not only determine the flow and credibility of information but also shape the level of trust within the network, serving as key drivers of social contagion – a phenomenon where the behaviour of an individual is influenced by the actions and interactions of others within the social network (Van den Bulte & Lilien, 2001; Rishika & Ramaprasad, 2019). Consequently, these network characteristics are expected to influence the broader dissemination of information, ultimately steering user behaviour and participation within the community, all of which can directly affect follower transfer to the brand (Wang et al., 2022). Indeed, influencers who occupy central positions within their networks can attain increased visibility and exert greater influence (Himelboim & Golan, 2023). Furthermore, the strength of an influencer's connections fosters a sense of community and trust among followers, which are critical for driving conversions (Xiong et al., 2018). Additionally, the nature of the content shared by influencers can attract followers and encourage them to follow the sponsored brand (Foroughi et al., 2024).

3.2. Hypotheses development

To explore the characteristics and behaviours of influencers within their social networks that hold the greatest potential in driving the growth of a brand's social network, we formulate four hypotheses grounded in the SN theory. These hypotheses guide the research towards gaining a deeper understanding of the interactions and relationships between influencers and non-brand followers during new product launch events. The subsequent sections provide a detailed explanation of each hypothesis.

3.2.1. Interaction frequency

Social media platforms are intentionally designed to foster conversations between individuals, emphasizing the critical "social" aspect of social media (Iyer & Katona, 2016).

As opinion leaders, influencers play a critical role in communicating and interacting with large audiences, acting as intermediaries between brands (or media) and the public (Ooi et al., 2023). They prioritize interaction to leverage their influence and actively engage followers (Jun & Yi, 2020). Interaction between influencers and followers occurs when an influencer actively interacts with his/her followers and attracts their participation through likes, shares, private and/or public messages, etc., resulting in continuous communication (De Vries et al., 2012). This interaction allows users to express their emotions, opinions, and experiences, creating a sense of intimacy and stability in their relationship with the influencer (Jun & Yi, 2020).

The frequency of interactions is a key determinant of the relationship strength between a focal actor and other nodes within the social network (Dai et al., 2021; Granovetter, 1973; Wang & Chiang, 2009; Xiong et al., 2018). On the one hand, frequent interactions create the perception that influencers are genuinely passionate about their work and sincerely engaged with their followers, responding personally and communicating in real-time. In essence, this interaction is assumed to be driven by authentic intrinsic motivation (Jun & Yi, 2020). On the other hand, a high level of interaction prompts followers to feel actively engaged in the relationship, motivating them to readily share their thoughts and opinions with the influencer (Jun & Yi, 2020). This user-to-user interaction enhances the assimilation of information (Zhuang et al., 2023). When followers develop a strong emotional connection with the influencer through interaction, they are more likely to follow his/her suggestions. Therefore, active interactions between influencers and followers enhance followers' trust in the sponsored brand, reinforcing its perceived ability to deliver benefits (Jun & Yi, 2020). Several empirical studies also suggest that many interactions can foster user engagement, encompassing both behavioural and attitudinal actions toward brands (Pentina et al., 2018). This engagement ultimately contributes to a more favourable perception of the brand (Juntunen et al., 2020; Ooi et al., 2023). Accordingly, we formulate our first hypothesis as follows:

H1: *The more an influencer interacts with his/her followers, the higher the number of followers who will start following the sponsored brand, thereby facilitating the growth of the brand's network.*

3.2.2. Popularity

Popularity has been extensively studied as a precursor to digital influence (Conde & Casais, 2023; Ladhari et al., 2020). High levels of popularity can mould users' opinions, attitudes, and beliefs, consequently impacting their purchase intentions (Zhuang et al., 2023). An influencer's popularity is typically measured by the reception and reach of his/her posts (Cheung et al., 2022; Pittman & Abell, 2021; Antoniadis et al., 2019). When an influencer's posts reach a broad audience beyond his/her immediate follower base, it indicates widespread recognition and influence within his/her niche or industry. Therefore, evaluating the reception and reach of an influencer's posts can provide valuable insights into his/her level of popularity and impact within the digital landscape (Cheung et al., 2022; Antoniadis et al., 2019).

On social media, users can like, retweet, and comment on influencers' posts (Hughes et al., 2019). Likes are a simple yet powerful way for users to show their appreciation or approval of an influencer's post. By liking a post, users signal a positive response to the content and provide social recognition to the influencer (Dong et al., 2021; Li, 2018; Cai et al., 2020). Retweets (on Twitter) or shares (on other social media platforms) allow users to forward the influencer's post to their followers. Sharing content essentially endorses and validates its value, creating a cascading effect as the post reaches a wider audience. This ripple effect increases the influencer's exposure and credibility while enhancing the sponsored brand's visibility (Malhotra et al., 2012). Comments enable users to express more detailed feelings, thoughts, or opinions about an influencer's post (Swani et al., 2017). Unlike likes and retweets, they provide a space for interaction (Devereux et al., 2020). Users can comment positively or negatively on branded posts. Positive comments can enhance the value of the post, whereas critical comments may generate (potentially detrimental) discussions and debates (De Vries et al., 2012). From the perspective of SN, likes, retweets, and comments can represent varying types of ties within the network, reflecting different levels of relational strength (Liu et al., 2017).

These indicators are widely regarded as reliable measures of the popularity and overall favourability of both posts and the influencers behind them (De Vries et al., 2012; Karagür et al., 2022; Zhuang et al., 2023). Prior research has consistently supported this notion, revealing that a post's popularity on social media is directly linked to the extent of likes, shares, and comments it generates (De Vries et al., 2012; Robson & Banerjee, 2023; Lahuerta-Otero et al., 2018; Zhang et al., 2014). These findings emphasize that a user's response to an influencer's post is not driven solely by the content itself but also by how other users have reacted. In this context, popularity metrics hold significant value, enhancing the persuasive power of influencers (Kay et al., 2020). Consumers often rely on these metrics to assess the credibility, reliability, and likability of a source, ultimately influencing their opinions, attitudes, and behaviours (Kay et al., 2020; Kay et al., 2023).

Consequently, the aggregate popularity of branded posts shared by an influencer can effectively redirect followers' attention toward the endorsed brand, generating increased interest in the brand (Juntunen et al., 2020). This interconnected relationship between popularity metrics, influencer persuasion, and consumer behaviour highlights the crucial role influencers play in driving brand exposure and engagement within their online communities. Accordingly, our second hypothesis unravels as follows:

H2: *The greater the popularity of an influencer's posts, the higher the number of his/her followers who will start following the sponsored brand, thereby facilitating the growth of the brand's network.*

3.2.3. Network position

SN theory suggests that influencers and opinion leaders can be discerned by their position in the network (Goldenberg et al., 2009; Himelboim & Golan, 2023).

Influencers typically fall into two categories: social hubs and social bridges (Hinz et al., 2011). Social hubs are well-connected people with a high number of connections to others. They have a high degree centrality, measured by the number of direct connections to other individuals within the network (Freeman, 1978). Social hubs have a large and engaged follower base, enabling them to communicate regularly with their contact group. This advantage allows them to gain valuable insights into the expectations and preferences of their audience (Wang et al., 2022). Their network position not only amplifies the visibility of the information they disseminate but also incentivizes the production of content that aligns closely with audience needs, further reinforcing their influence (Wasko & Faraj, 2005). In contrast, social bridges act as intermediaries, linking unconnected groups within the network (Hinz et al., 2011). Their role as connectors enables the seamless transmission of information and influence across diverse and segmented audiences (Zhang & Luo, 2017; Cross et al., 2006; Ma & Zhang, 2022). This information control advantage reinforces their credibility and influence, as they become a means for the exchange of valuable insights and content between different network segments (Burt, 2021; Gulati, 1998). As a result, they can effectively amplify the reach and impact of the content they share, enhancing engagement and fostering stronger connections with their diverse audience (Himelboim & Golan, 2023; Wang et al., 2022). Social bridges have a high betweenness centrality, which measures how often an individual lies on the shortest paths connecting other members of the network (Freeman, 1978).

Accordingly, we formulate the following two hypotheses:

H3.a: *The higher the number of direct connections an influencer has within the network (social hub position), the higher the number of his/her followers who will start following the sponsored brand, thereby facilitating the growth of the brand's network.*

H3.b: *The higher the centrality of an influencer within the network (social bridge position), the higher the number of his/her followers who will start following the sponsored brand, thereby facilitating the growth of the brand's network.*

3.2.4. Influencer-generated content type

Influencers regularly create content on social media in their areas of specialisation, disseminating persuasive messages that combine informational and entertainment value to promote a brand or product (Lou & Yuan, 2019; Foroughi et al., 2024). Consumers are driven by information-seeking behaviour on social networking sites, relying on influencers' content to aid their decision-making processes (De Vries et al., 2012; Herrando & Martín-De Hoyos, 2022). Understanding the content type of network ties is crucial for grasping the complexity and interconnectedness of social relationships (Tichy et al., 1979). By analysing the type of content shared – whether informative or hedonic – it becomes possible to discern the different layers of interaction that shape social networks (Bracke, 2016).

To attract and retain their followers on social media, influencers consciously and consistently produce and share informative content (Misra et al., 2024). Informative content provides their followers with general information (informational value) about a brand (Hamzah et al., 2021; Luarn et al., 2015), product specifications, and technical knowledge concerning product attributes (Tafesse, 2015). Informers offer utilitarian value to their audience, which is crucial during the purchase decision-making process (Ren et al., 2023). Influencer-generated content is often perceived as more authentic than brand-generated content (Koay et al., 2022), as it incorporates both functional (e.g., product features) and personal (e.g., the influencer's experience with the product) elements (Sánchez-Fernández & Jiménez-Castillo, 2021). By delivering informative content, influencers establish themselves as reliable sources of information within their follower base. This credibility fosters a sense of trust among their followers, making them more receptive to the influencers' recommendations and endorsements (Lou & Yuan, 2019). Moreover, the informational value of the content plays a pivotal role in driving consumer engagement, increasing brand awareness, and ultimately influencing purchase intentions (Lou & Yuan, 2019; Menon et al., 2019; Paul et al., 2024). Accordingly, we hypothesize:

H4.a: *The higher the percentage of an influencer's posts with informational value, the higher the number of his/her followers who will start following the sponsored brand, thereby facilitating the growth of the brand's network.*

Furthermore, influencers are adept at infusing their posts with personal aesthetic touches, providing entertainment value for their followers (Lou & Yuan, 2019; Foroughi et al., 2024). This often includes captivating images, engaging videos, and other creative elements that make the content enjoyable (Hamzah et al., 2021). Entertainers deliver hedonic value by creating immersive, experiential engagement that is both enjoyable and playful (Ren et al., 2023; Lin et al., 2018; Bazi et al., 2023).

However, while entertainment value adds to the overall experience generated by the communication, it may not necessarily foster followers' trust in brand posts and stimulate purchase intentions toward the sponsored brand (Lou & Yuan, 2019; De Vries et al., 2012; Lou & Xie, 2021; Foroughi et al., 2024). Entertainment-oriented posts frequently feature content unrelated to the sponsored brand. However, during the pre-consumption phase, consumers are generally more inclined to seek information about the brand or product rather than purely entertaining content (Demmers et al., 2020; Foroughi et al., 2024; Liu & Zheng, 2024). Accordingly, we hypothesize:

H4.b: *The higher the percentage of an influencer's posts with entertainment value, the fewer the number of his/her followers who will start following the sponsored brand, thereby facilitating the growth of the brand's network.*

Fig. 1 summarizes our hypotheses on the determinants of followers' transfer to the brand's social network. Typical control variables are also included in the conceptual framework, as explained in the next section.

4. Data & methods

4.1. Research setting

Our study is set in the gaming market, one of the fastest-growing industries with a significant presence on social media. Marketers in this context increasingly rely on influencers to endorse a wide range of products, including video games, gaming accessories, apparel, sports beverages, and various merchandise (Church, 2022). For our analysis, we focus on Twitter – recently rebranded as X – which serves as a hub for numerous gaming conversations, with over 1.5 billion tweets discussing gaming in 2021. It is opening the doors for brands looking to engage with the most influential gamers and gaming fans worldwide.

In this study, we examine the launch events of three new video games: *Final Fantasy VII Remake* (FF7R), *Elden Ring* (ER), and *God of War Ragnarok* (GoW).

FF7R is an action Role-Playing Game (RPG) developed and released by Square Enix on April 10, 2020, exclusively for PlayStation 4 (PS4). It combines real-time action with role-playing elements. Within three days of its release, FF7R achieved remarkable sales, surpassing 3.5 million copies worldwide. By the three-month mark, total sales, including both retail and digital channels, exceeded 5 million copies.

ER is an action RPG video game developed by the Japanese software house FromSoftware and published by Bandai Namco Entertainment on February 25, 2022. Within three weeks, ER sold 12 million units, and by June 2022, its cumulative sales had surpassed 16.6 million units.

Lastly, GoW, developed by Santa Monica Studio and published by Sony Interactive Entertainment, made a global impact on its cross-generation release, hitting both PS4 and PS5 on November 9, 2022. It became the fastest-selling first-party launch game in PlayStation history, surpassing 11 million copies by the three-month mark. The captivating storyline and thrilling action sequences of GoW deeply resonated with the community.

In our study, we designated these three video games as the focal brands under investigation, with their official Twitter profiles serving as reference brand profiles. This choice was based on the recognition that within the gaming industry, as in other business domains, the brand is intrinsically intertwined with the product, often becoming indistinguishable in the eyes of the consumers. Indeed, in this context, it is commonplace for companies to employ a multi-branding strategy for their products. This strategy entails assigning a unique brand identity to each product, ensuring that each one is trademarked with its distinct name, logo, and other defining elements. When a video game is launched, its branding extends beyond mere visuals to encompass the entire gaming experience, including narrative, graphics, gameplay, and community engagement. This holistic approach ensures that the brand not only reflects the product's identity but also distinguishes it within the market. Consequently, the success or failure of these games significantly impacts the brand's image. Moreover, on platforms like Twitter, game developers or producers establish official game profiles and hashtags to communicate with the gaming community, provide updates, and engage with fans. These profiles serve as authoritative sources for

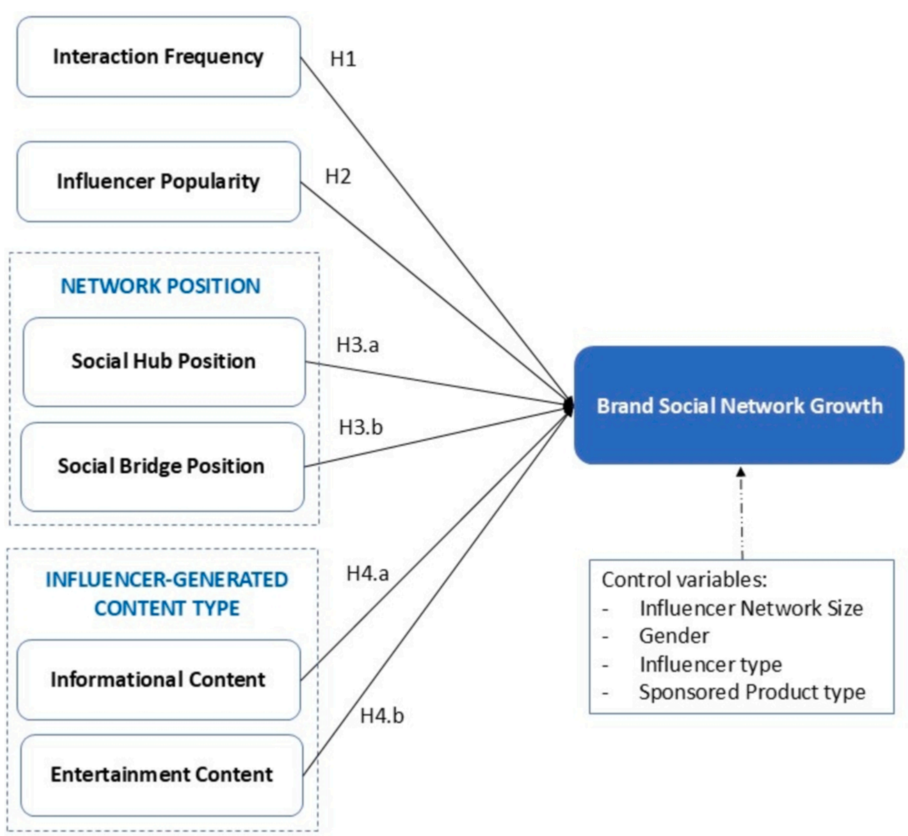

Fig. 1. Conceptual Framework.

game-related information, further solidifying the interdependence between brand perception and community engagement.

4.2. Data collection

To test our hypotheses, we conducted extensive data collection by gathering tweets featuring official hashtags related to three video games before and after their respective launch: #FF7R, #EldenRing, and #GodofWarRagnarok. The data collection period for each video game spanned from 20 days before its release date until one month after. The decision was prompted by the significant increase in the volume and frequency of tweets about the game, beginning approximately 20 days before the launch. Indeed, preliminary observations over two months revealed that the volume and frequency of tweets were negligible before this window. Our choice is largely consistent with existing literature in analogous contexts, such as the movie industry (Divakaran et al., 2017; Duan et al., 2008; Gelper et al., 2018; Karniouchina, 2011; Liu, 2006). Specifically, the data collection period for FF7R spanned from March 21 to May 10, 2020, for ER from February 5 to March 27, 2022, and for GoW from October 20 to December 9, 2022. This timeframe was chosen because social media buzz and influencers' activity surrounding a new video game typically arise only shortly before and shortly after its launch. Even the emergence of video game influencers is a phenomenon that occurs for a limited time before and after the video game launch. Accordingly, our goal is to capture user discussions during the initial hype surrounding the game and minimize any potential (confounding) effects on the brand's social network that were not directly related to the selected influencers. It is worth noting that as we move further away from the launch period, the impact of the chosen influencers is likely to decrease, while other unobserved factors may start exerting greater influence, increasing endogeneity bias concerns. Similarly, extending to much earlier periods than the launch would not be sensible because very limited buzz or no buzz at all will manifest in those periods and even influencers would be hardly identifiable.

The resulting dataset was quite large, comprising over 800,000 tweets for #FF7R, exceeding one million tweets for #EldenRing and 450,000 tweets for #GodofWarRagnarok. To retrieve the dataset, we used the Rtweet package within the R software.

The data collection procedure for each video game is described below.

During the pre-launch phase (which started 20 days before the launch), we performed a daily collection of all tweets (original posts and retweets) featuring the official hashtag of each video game. This included various information about tweets and authors. Details are shown in Table 1.

Table 1
Collected information.

Name	Description
Tweet Date	Date of the tweet's creation
Tweet Content	Content of the tweet
Language	Language of the tweet
Tweet Likes	Number of likes received by the tweet
Tweet Retweets	Number of retweets received by the tweet
Is_Retweet	TRUE if the tweet is a retweet, FALSE if it's an original post
Author ID	Twitter handle of the tweet's author
Author Name	Name of the tweet's author
Author ID of Original Post	Twitter handle of the original post's author (if the tweet is a retweet)
Author Name of Original Post	Name of the original post's author (if the tweet is a retweet)
Date of Twitter Profile Creation	Date when the author's Twitter profile was created
Short Bio	Author's short bio on Twitter, including demographic information such as age, gender, location, and role, when available
Verification Status	TRUE if the author's profile is verified, FALSE otherwise
Followers	Number of followers of the tweet's author
Followees	Number of users followed by the tweet's author
Author Likes	Total number of likes received by the tweet's author
Author Retweets	Total number of retweets received by the tweet's author
Author Tweets	Total number of tweets posted by the tweet's author

Additionally, we extracted the list of followers for both the tweet authors and the selected video games (FF7R, ER, or GOW), a crucial step for assessing follower transfer. We excluded authors being essentially news outlets or companies, as they were beyond the scope of our study on individual influencers. Similarly, authors without followers were removed from the dataset, as their absence hindered our ability to measure follower transfer to the brand social network.

As the launch date approached, we identified influencers among the tweet authors. To do so, we first constructed a tweet-based network using data collected during the pre-launch phase. In this network, nodes represent the authors of the tweets (both original posts and retweets), while the edges represent the interactions between them, expressed through retweets. Each edge is weighted based on the number of retweets between the two users, with directionality established from the retweeter to the original post author. Leveraging this network, we computed Betweenness Centrality (BC) and Degree Centrality (DC), renowned Social Network Analysis (SNA) parameters serving as robust indicators of leadership or opinion influence (Hansen et al., 2011; Wasserman and Faust, 1994). Influencers were then selected based on their simultaneous ranking within the 95th percentile for DC, BC, and the number of followers, aligning our approach with the methodology proposed by Litterio et al. (2017). These selection criteria aimed to identify users with significant potential influence within the network. As a result, we identified 40 influencers for FF7R, 59 for ER, and 98 for GoW.

Throughout the post-launch phase, spanning 30 days, we closely monitored the selected influencers and the brand to observe their evolution over time. This involved a daily collection of all tweets containing the official game hashtag, alongside relevant information. The collected data were then cumulatively integrated into the previously constructed tweet-based network, which dynamically expanded and evolved as new original tweets and retweets were incorporated. This enabled us to compute the SNA metrics for evaluating influencers in the subsequent phase. Importantly, our evaluation of selected influencers encompassed data collected throughout the monitoring period, from 20 days before the launch until one month later. In addition, we systematically updated the follower lists of both influencers and the brand. Notably, during this monitoring phase, we conducted regular assessments to ensure that the selected influencers maintained their status as influencers, following the methodology previously described.

4.3. Variables and operationalization

In this section, we provide a detailed description of the dependent variable (§ 4.3.1), independent variables (§ 4.3.2), and control variables (§ 4.3.3), along with relevant descriptive statistics (§ 4.3.4).

4.3.1. Dependent variable

To estimate the impact of influencers on the follower growth of the sponsored brand's social network, we operationalized the dependent variable as *relative follower transfer* (RFT). This metric quantifies the proportion of the focal influencer's followers who began following the sponsored (video game) brand after the influencer's endorsement. Specifically, RFT is calculated as the ratio between the number of influencer followers who began following the brand during the monitored period (of course, after the brand was sponsored by the influencer) and the influencer's average number of followers during the same period. To measure the RFT numerator, we used a systematic matching process between the follower lists of each influencer and the brand, with both lists regularly updated during the observation window starting from the influencer's first post about the brand. When an influencer's follower, who at the beginning of the observation period was not a follower of the brand, also appeared on the brand list of followers, he/she was then classified as a transfer due to the influencer's promotion and added to the transfer count. Followers unique to either the influencer or brand lists were excluded from this count.

Fig. 2 enhances the conceptual clarity of the RFT measure by illustrating a scenario involving a brand (B, represented by a blue circle) and an influencer (I, depicted as an orange circle) during B's product launch at time t1, with I endorsing B. At time 0 (before the initiation of the new product launch), B's network encompasses 6 followers, comprising 4 exclusive followers (F1, F2, F3, and F4) and 2 followers shared with I (F6 and F7). Conversely, I's network encompasses two shared and 5 exclusive followers (F8, F9, F10, F5, F11). Subsequently, at t2, following the product release and I's promotional effort for B's product on his/her social media channel, it is reasonable to hypothesize that both B's and I's networks have transformed. Specifically, both B and I have acquired new exclusive followers (F12 for B and F14 and F13 for I). Furthermore, I's actions have resulted in the transition of certain followers from I's network to become also followers of B (F8, F9, F5).

This helps estimate the extent to which the behaviour and characteristics of I contribute to follower migration from I's network to that of B, thereby expanding the set of shared followers.

4.3.2. Independent variables

To test our hypotheses, we defined a set of independent variables. For hypothesis H1, we introduce the *Interaction Rate (IR)*, which assesses the frequency of an influencer's interactions with his/her audience and the resonance of his/her content with followers. (Ouvrein et al., 2021). More specifically, this variable quantifies the number of interactions generated per unit of posts and followers the focal influencer is able to stimulate, where the overall interactions are computed as the sum of likes and retweets.[2] Mathematically:

$$IR = \frac{Likescount + Retweetcount}{Originalpostcount} \times \frac{100\%}{Averagefollowers}$$

Likes count, retweets count, original posts count, and average followers are computed over the monitoring period from 20 days before the launch to one month thereafter. Specifically, the likes count measures the total number of likes received by the influencer, while the retweets count indicates the total number of times the influencer's posts were retweeted. Additionally, the original posts count represents the total number of posts shared by the influencer, and the "average followers" metric reflects the mean number of followers the influencer had during the specified period.

To test our hypothesis H2, following Hughes et al. (2019), we assessed the influencer's popularity based on the total number of likes he/she received from 20 days before the game launch until one month afterwards. This value was then adjusted by dividing it by the number of followers (*N° Likes/Avg Flw*). By utilising this metric, we can gauge the level of appreciation an influencer receives from his/her network during the specific period under observation. Indeed, a higher value indicates greater audience appeal and positive reception.

To measure the network position of an influencer (our hypotheses H3.a and H3.b), we relied on two key SNA metrics, namely *DC* and *BC,* discussed above (Wasserman & Faust, 1994; Hansen et al., 2011). Specifically, DC serves as a measure of the social hub position within the network. It is computed by counting all incoming and outgoing edges (retweets), for each influencer node within the overall tweet-based network established from 20 days preceding the video game launch to one month afterwards. On the other hand, BC evaluates the role of an influencer as a social bridge and facilitator of the flow of information or interactions between different nodes in the network. That is, it quantifies the extent to which the influencer acts as a bridge or intermediary, connecting disparate parts of the network. This metric is computed by quantifying the number of shortest paths passing through each influencer node within the overall tweet-based network (where, again, nodes are users and edges retweets) established from 20 days before its launch until one month later. A higher BC indicates that the influencer frequently lies on the shortest path between other nodes, thus well reflecting his/her role as a hub connecting different parts of the network and controlling the flow of information or influence. Both metrics were divided by the number of nodes in the network of the corresponding video game. This process enables a fair comparison of centrality metrics across networks of different video games with varying sizes, ensuring an accurate evaluation of influencer importance within his/her specific context.

Finally, to examine the type of content shared by influencers (our hypotheses H4.a and H4.b), we introduced two variables: *Tweets with Informational Value (TIV)* and *Tweets with Entertainment Value (TEV)*. To calculate the TEV and TIV variables, our team meticulously analysed all tweets from the 197 influencers. Tweets containing informative content, such as general information, clarifications, countdowns to video game launches, release dates, and pre-order instructions, were classified as "Informative". Similarly, tweets featuring multimedia elements like videos, images, audio, GIFs, or external links for humour and entertainment were categorized as "Entertainment". Tweets containing both types of content received both labels, while those lacking either attribute were left unlabelled. After this categorization, we computed the TIV variable as the ratio of "Informative"-labelled posts to the total number of posts generated by each influencer from 20 days before the launch until one month later. Similarly, the TEV variable was calculated as the ratio of "Entertainment"-labelled posts relative to the total number of generated posts during the same period.

4.3.3. Control variables

We incorporated several control variables related to the influencer's characteristics, as these factors have been shown to impact consumer behaviour and their inclination to follow influencers (Peters et al., 2013; Chu & Kim, 2011). First, the size of an influencer can be important in demonstrating his/her impact (Peters et al., 2013), as it establishes the influencer's maximum potential reach. To account for this, we introduced the *Average Number of Followers (ANF)*, representing the average number of individuals following the influencer from 20 days before the launch until one month after, and the *Average Number of Followees (ANFE)*, representing the average number of individuals who are followed by the influencer from 20 days before the launch until one month after. Second, the influencer's gender has generally been viewed as influential, with studies indicating that consumers tend to establish unique perceptions and connections based on the gender of the influencer (Knoll & Matthes, 2017; Vaiciukynaite, 2019; Hudders & De Jans, 2022; Leung et al., 2022). Accordingly, we included a binary variable, denoted as *GENDER*, indicating whether the influencer self-identifies as female or male. Third, studies highlight the importance of the influencer's expertise and affinity with followers as critical social factors influencing consumer engagement and attitudes toward sponsored brands (Chu & Kim, 2011). Therefore, controlling the type of influencer is important because individuals are often more inclined to follow influencers perceived as experts in a particular field (Juntunen et al., 2020). To do so, we created a binary variable indicating whether the influencer self-identifies as a gamer (*INF_TYPE*). This identification was determined by the presence of videos showcasing the influencer playing the game. Finally, unobserved characteristics within different product typologies and the associated user communities may lead to variations in influencer behaviour and his/her impact on the brand's social network growth (De Veirman et al., 2017). To account for this, we introduced three dummy variables – *Game Type (GT)* 1 (FF7R), 2 (ER), and 3 (GoW). Including two of these variables (the remaining one is considered the baseline) allows us to examine whether the level of RFT is game-contingent.

[2] https://www.quintly.com/.

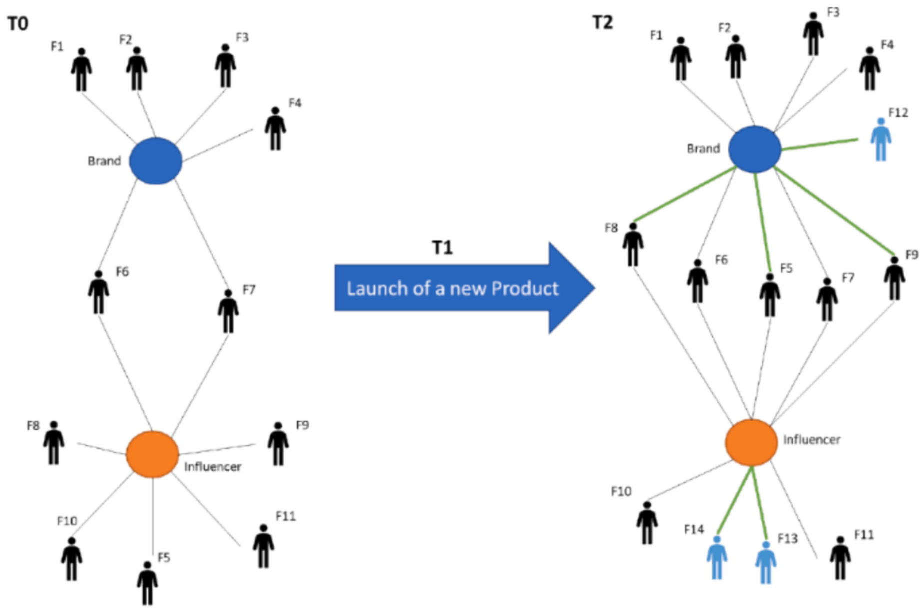

Fig. 2. Evolution of influencer and brand social networks during a product launch event.

4.3.4. *Descriptive statistics*

Table 2 reports the descriptive statistics for the full sample (197 observations). On average, the identified influencers are micro-influencers with more than 10,000 followers. The ratio between the average number of followers and followees is on average quite higher than 1, indicating high-quality influencers. We can also observe a predominance of tweets with entertainment content. This could be attributed to the fact that, in the gaming world, influencers often share videos of themselves playing video games or redirect users to their other social channels, such as Twitch and YouTube. Finally, Table 2 indicates that many influencers exhibit a higher BC than DC. This suggests that these influencers often prioritize acting as intermediaries in broadcasting and disseminating information, rather than focusing on establishing extensive direct connections. However, it is worth noting that this strategic preference is not a one-size-fits-all scenario, as evidenced by the broad range of BC values observed.

Table 3 displays the descriptive statistics for each variable across individual video games. While no significant disparities were observed across the games, some interesting insights emerged. Notably, FF7R influencers exhibit higher BC, potentially signalling their role as key intermediaries fostering information flow. Both FF7R and GOW influencers exhibit a higher number of TIV, albeit lower than entertainment-focused ones. GOW influencers stand out with slightly higher average Likes/Avg Flw and DC. In contrast, ER influencers show a slightly higher IR value, indicating more frequent interactions with their audience. The values of average size and relative follower transfer are comparable, with ER influencers having slightly higher averages of ANF and RFT compared to FF7R. The opposite occurs concerning ANFE.

Table 2
Descriptive statistics.

Variable	Mean	SD	Min	Max
RFT	0.0075	0.0005	0	0.0536
ANF	11111.5	21985.3	30.5	192,239
ANFE	1418.1	2443.4	5	22,063
N° Likes/Avg Flw	0.5013	1.2968	0	10.1444
IR	0.0888	0.293	0	2.9331
DC	0.0103	0.0326	0	0.2696
BC	19.6202	64.6641	0	580.639
TIV	0.1449	0.0158	0	1
TEV	0.5049	0.0246	0	1

Before embarking on the empirical analysis, it is paramount to highlight the absence of any serious multicollinearity concerns, as can be observed from the correlation matrix (Table 4).

5. Empirical analysis

5.1. *Main results*

To test our hypotheses, we employ a robust linear regression model. Logarithmic transformations are applied to variables exhibiting skewness. The results of the OLS model are presented in Table 5.

Among the control variables, the type of influencer significantly and positively influences the relative follower transfer from the influencer network to the brand's social network. This indicates that users are more inclined to trust and follow influencers with expertise in the field (e.g., gamers in our setting). On the other hand, the average number of followees shows a significant but negative correlation with the dependent variable. The results suggest that having many followees can hinder the transfer of followers. This may be due to users perceiving the influencer as a spammer who follows a multitude of people, including non-friends and non-family members, with the expectation of receiving reciprocal follows (Khalil et al., 2017). Additionally, the type of game impacts the transfer results, with both video games FF7R and GoW exhibiting lower-quality follower transfers compared to ER. Quite interestingly, the number of followers does not have a significant effect on the relative follower transfer.

Moving to our hypotheses, three of them were supported (H1, H2, and H3a), while the remaining hypotheses did not yield significant results (H3b, H4a, and H4b). Specifically, the relative follower transfer is positively influenced by the influencer *IR*. This implies that more frequent interactions between influencers and their audience lead to a greater transfer of followers from the influencer's network to the brand's social network, as suggested by H1. Moreover, the popularity of the influencer's posts, measured by the total number of likes relative to the number of followers during the observed period, plays a crucial role in the follower transfer to the brand's social network, supporting our hypothesis H2.

Regarding our hypotheses H3.a and H3.b, the results show that *DC* is significant and positively correlated with the dependent variable, supporting H3.a. This implies that influencers with a higher degree of centrality in the network are more likely to facilitate follower transfers

Table 3
Descriptive statistics per video game.

Variable	FF7R				ER				GoW			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
RFT	0.0082	0.0050	0.0002	0.0173	0.0126	0.0068	0.0020	0.0405	0.0043	0.006	0	0.0536
ANF	9083.1	10891.3	2230	50,743	12428.6	22949.2	1454	120,491	11059.6	24223.6	30.5	192,239
ANFE	1564.5	1712.4	31	9329	1453.6	2759.5	5	20,127	1349.01	2483.12	16	22,063
N° Likes/Avg Flw	0.3376	0.7727	0	4.082	0.2964	0.802	0	5.254	0.6706	1.607	0	10.1444
IR	0.0321	0.0695	0	0.4055	0.1101	0.4257	0	2.9331	0.096	0.245	0	1.8153
DC	0.0091	0.0407	0	0.2429	0.0085	0.0299	0	0.203	0.0117	0.0312	0	0.2696
BC	12.3	43.7	0	210.3	0.0041	0.0165	0	0.09	33.02	83.1	0	580.639
TIV	0.1866	0.0316	0	0.5882	0.0638	0.0163	0	0.5714	0.176	0.0256	0	1
TEV	0.5388	0.045	0	1	0.4542	0.0516	0	1	0.5217	0.0335	0	1

Table 4
Correlation matrix.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) AFO	1										
(2) AFR	0.31**	1									
(3) IR	−0.06	−0.12+	1								
(4) BC	0.19+	−0.02	0.02	1							
(5) DC	0.13+	−0.08	0.21*	0.20*	1						
(6) N° Likes/Avg Flw	−0.04	−0.12	0.29**	0.15*	0.27**	1					
(7) TIV	−0.12+	−0.01	−0.05	−0.03	−0.09	−0.01	1				
(8) TEV	0.13+	0.10	0.22**	−0.04	0.16*	0.15*	−0.23**	1			
(9) INFTYPE	0.03	0.16*	−0.08	−0.07	0.15*	0.01	0.05	0.08	1		
(10) GT1	−0.04	0.03	−0.09	−0.05	−0.01	−0.06	0.09	0.05	0.03	1	
(11) GT3	−0.02	−0.03	0.02	0.20**	0.04	0.13+	0.15*	0.05	−0.17*	−0.28**	1

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5
OLS regression model results.

Variable	Coefficient (Robust standard errors)
IR	0.269* (0.129)
N° Likes/Avg Flw	0.152* (0.081)
DC	0.242* (0.099)
BC	−0.117 (0.093)
TIV	−0.001 (0.065)
TEV	−0.006 (0.023)
ANF	0.020 (0.072)
ANFE	−0.193* (0.098)
INFTYPE	0.043** (0.015)
GENDER	−0.007 (0.020)
GT1	−0.066** (0.023)
GT3	−0.148*** (0.018)
Constant	0.206*** (0.024)
N° of observations	197
R^2	0.441

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

to the brand's social network. Conversely, *BC* is not significant in the model, providing no support for our H3.b. Therefore, acting as a bridge between different network segments does not guarantee a substantial transfer of the influencer's followers to the brand's social network.

Finally, H4.a and H4.b are not supported, as the corresponding variables are largely insignificant, suggesting that neither type of content (informative or entertaining) vehiculated by the influencer seems to be sufficient to drive follower transfers to the brand's social network. Instead, follower transfer appears to be more influenced by the number of reactions a post receives than by its specific content type.

Taken collectively, our findings suggest that to generate follower transfers to the brand's social network, influencers should prioritize frequent audience interactions, achieve high popularity, and occupy a central, hub-like position within their social networks.

5.2. Robustness checks

In this subsection, we present the results of the Variance Inflation Factor (VIF) analysis derived from the OLS model (see Table 6). The analysis confirms the absence of multicollinearity issues, as all VIF values are below the widely accepted threshold of 10.

Furthermore, we show the robustness of our results by using two alternative regression models. In particular, we employed a Generalized Linear Model (GLM) with a logit link and binomial family, which is a widely used regression model for analysing data where the dependent variable is a percentage (in the range [0,1], essentially), as in our case (McCullagh, 2019).

The second model we used is the Tobit model, which is designed to estimate linear relationships between variables when the dependent variable is subject to left- and/or right-censoring. In our case, the dependent variable is meaningful only in the range [0,1]. Table 7 shows the results from both GLM and Tobit models. As can be noticed, these results are fully consistent with those in Table 5. This confirms the robustness of our findings, as hypotheses H1, H2, and H3.a continue to be supported.

Finally, we further employed the OLS model on a reduced dataset (n

Table 6
VIF analysis results.

Variable	VIF value
ANF	1.30
ANFE	1.29
N°Likes/Avg Flw	1.96
IR	1.87
DC	1.52
BC	1.29
TIV	1.18
TEV	1.23
INFTYPE	1.17
GENDER	1.13
GT1	1.51
GT3	1.65

Table 7
Results of GLM (with logit link and binomial family) and Tobit regression models.

Variable	Coefficient (Robust standard errors) for GLM	Coefficient (Robust standard errors) for Tobit
IR	0.269* (0.129)	0.276* (0.136)
N° Likes/Avg Flw	0.152* (0.081)	0.156* (0.085)
DC	0.242* (0.099)	0.241* (0.105)
BC	−0.117 (0.093)	−0.099 (0.098)
TIV	−0.001 (0.065)	−0.008 (0.070)
TEV	−0.006 (0.023)	−0.005 (0.024)
ANF	0.020 (0.072)	0.038 (0.097)
ANFE	−0.193* (0.098)	−0.206* (0.104)
INFTYPE	0.043** (0.015)	0.044** (0.016)
GENDER	−0.007 (0.020)	−0.005 (0.021)
GT1	−0.066** (0.023)	−0.065** (0.024)
GT3	−0.148*** (0.018)	−0.163*** (0.019)
Constant	0.206*** (0.024)	0.204*** (0.026)
N° of observations	197	197
R^2	0.447	–
+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.		

= 157), for which influencer location is available and thus can be included as an additional control variable,[3] as shown in Table 8. The results of this analysis reveal that this control variable is not significant, while the variables of interest – namely, IR, Like/avg flw, and DC – maintain their significance, thus providing further confirmation for hypotheses H1, H2, and H3a.

6. General discussions

6.1. Summary and discussion of main findings

In this study, we conducted an empirical analysis to investigate the impact of influencer characteristics and behaviours within his/her network on the growth of the sponsored brand's social network, drawing insights from three cases of new video game launches on Twitter.

First, our findings indicate that frequent interactions between influencers and their followers significantly enhance user engagement and facilitate the transfer of followers to the brand's social network. This underscores the prevailing notion that when influencers actively interact with their followers through diverse forms – such as responding to comments, initiating conversations, and sharing content via likes and retweets – they foster a sense of connection and profound involvement (Jun & Yi, 2020; Ooi et al., 2023). Such interactions are likely to increase user attention, participation, and interest in both the influencer's content and the associated brand (Jun & Yi, 2020). This dynamic aligns with the principles of SN, which emphasize the importance of strong and frequent connections in facilitating effective information dissemination within a network (Liu et al., 2017; Wang & Chiang, 2009; Dai et al., 2021). Notably, our study extends this understanding by demonstrating that frequent interactions drive followers more effectively toward the brand, amplifying its network growth.

Second, our findings underscore that influencers positioned as social hubs within their networks are more effective in driving follower transfers to the brand compared to those positioned as social bridges (Valsesia et al., 2020). According to the SN theory, this strategic positioning not only amplifies the visibility of the information they disseminate but also fosters the creation of content that resonates deeply with audience preferences, thereby reinforcing their influence (Wang et al., 2022; Hinz et al., 2011). This supports the notion that when influencers with a substantial number of connections promote a brand, their endorsement has the potential to reach a wider audience. These influencers are perceived as authoritative figures and opinion leaders whose endorsements carry significant weight (Freberg et al., 2011; Casaló et al., 2020). Consequently, these dynamics enhance the likelihood of transferring existing followers from the influencer's network to that of the brand.

Third, our findings highlight the pivotal role of influencer popularity, as measured by the (aggregate) popularity of his/her posts, in fuelling brand growth, suggesting the greater importance of this feature compared to the content of the posts. Indeed, sponsored content that garners a high number of likes is often seen as more trustworthy, fostering positive attitudes toward the brand (Mattke et al., 2020). Furthermore, a high volume of likes amplifies content visibility and signals its relevance within the broader network. From the perspective of SN, it can be interpreted as a marker of tie strength, reflecting the depth of relational connections between influencers and their audience (Arnaboldi et al., 2013; Liu et al., 2017).

This finding contrasts with previous studies that emphasize post content as a primary driver of user behaviour (Lou & Yuan, 2019; Ki et al., 2020; Paul et al., 2024). While acknowledging the impact of content on user perceptions and responses, our results indicate that the sheer popularity of an influencer, as evidenced by the volume of likes garnered, holds greater sway over user behaviour. This may reflect a shift in user preferences as users are increasingly drawn to popular posts, seeking to align themselves with trending conversations (Chang et al., 2015). Interestingly, our findings also challenge the prevailing notion that an influencer's success is contingent on the size of their follower base (Peters et al., 2013; De Veirman et al., 2017). Our study suggests that the importance of a large follower count in achieving greater visibility and reach may not be as significant as previously argued (Wies et al., 2023). While having a large pool of followers can certainly contribute to an influencer's initial reach, our research reveals that follower count alone does not guarantee enhanced visibility, increased engagement, or follower transfer. Instead, factors such as the frequency of interactions, the popularity of posts, and the influencer's social hub position within the network appear to play a more pivotal role in driving brand growth. Finally, our findings supplement the existing literature on new product launches by highlighting the characteristics and behaviours of influencers within their social networks that significantly impact the diffusion of new products. In addition to the network position

Table 8
OLS regression model results controlling for influencer location.

Variable	Coefficient (Robust standard errors)
IR	0.295* (0.122)
N° Likes/Avg Flw	0.147* (0.089)
DC	0.295* (0.108)
BC	−0.166 (0.112)
TIV	0.021 (0.077)
TEV	−0.011 (0.028)
ANF	0.005 (0.081)
ANFE	−0.171 (0.131)
INFTYPE	0.042* (0.018)
GENDER	0.008 (0.024)
EUROPE	−0.006 (0.007)
ASIA	0.031 (0.071)
AMERICAS	0.036 (0.018)
GT1	−0.059* (0.027)
GT3	−0.161*** (0.022)
Constant	0.173*** (0.064)
N° of observations	157
R^2	0.467
+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.	

[3] We introduced four dummy variables — Europe, Asia, Americas, and Australia — to control for the diverse influencer locations. By incorporating three of these variables (with the fourth serving as a baseline), we can investigate the potential influence of the influencer's geographical position on the level of RFT.

emphasized in prior studies (Wei et al., 2023; Wang et al., 2023; Yang et al., 2023), we reveal that also influencer popularity and the frequency of interactions play critical roles in enhancing visibility, boosting promotional effectiveness, and ultimately driving brand growth.

6.2. Theoretical implications

This study marks one of the initial endeavours to investigate the characteristics and behaviours of the influencers within their social networks, quantifying their effects on brand follower growth, through real Twitter data analysis. It responds to the call by Vrontis et al. (2021) for more exhaustive inquiries into the intricate dynamics among influencers, users, and brands, aiming to unravel their complexities and implications for marketing strategies. In so doing, we shed light on influencer behaviours and characteristics that can foster the transfer of followers from the influencer network to that of the brand.

Our study carries substantial implications for the existing literature on influencer marketing. Previous studies have predominantly focused on the dynamics between influencers and consumers—providing valuable insights into influencer attributes and traits and their impact on consumer behaviour (Cheung et al., 2022; Zhou et al., 2023; Jun & Yi, 2020). Instead, our research takes a distinct perspective by shifting the focus towards the key characteristics and behaviours exhibited by influencers within their network that manifest a discernible impact on brand social networks. From this standpoint, a significant contribution of our study lies in the analysis of influencers through the lens of network dynamics, coupled with the introduction of objective measurement for calculating influencer ability in driving brand social network growth.

Furthermore, by harnessing real data extracted from Twitter, we transcend the traditional survey-based methodologies that have long dominated the existing literature (Campbell & Farrell, 2020; Lou & Yuan, 2019). The proposed data-driven approach not only bolsters the validity and robustness of our findings but also facilitates a more dynamic and comprehensive analysis of the relationships between influencers and their audiences within social networks. In so doing, we respond to the increasing calls for a more profound exploration of influencer marketing through the lens of big data (e.g., Sheth, 2021; Sheth & Kellstadt, 2021; Taylor & Carlson, 2021; Syrdal et al., 2023). These calls underscore the imperative to move beyond traditional methodologies and embrace the rich insights that big data can offer, particularly in elucidating influencer-followers dynamics and the effect on brands within digital contexts. Consequently, our study stands out as one of the academic investigations that exploit real-world secondary data to examine the impact of influencers' characteristics and behaviours within their social networks on the growth of followers for sponsored brands.

Moreover, we contribute to the SN theory by providing empirical insights into which network properties – specifically content, the nature and strength of connections, and the positioning of actors within the network (Tichy et al., 1979; Granovetter, 1973; Wang et al., 2022) – exert the most significant influence on the flow of information and the dynamics of influence within the network. Furthermore, this research strengthens the empirical foundation for applying SN principles to marketing research (Bonchi et al., 2011; Webster & Morrison, 2004). This approach offers a comprehensive perspective on influencers, analysing them not merely as isolated entities but as integral components of their networks, interacting with other users (Zhang et al., 2018; Litterio et al., 2017). Such an expanded view enables a more in-depth exploration of the relational dynamics at play, underscoring the critical role of relationship strength and network positioning in shaping influencer efficacy and driving brand growth (Wang et al., 2022).

Lastly, it is pertinent to underscore the contextual backdrop of our study, specifically the launch of a new product. In this scenario, the influencer assumes a pivotal role, wielding the potential to significantly impact the success or failure of both the promotional campaign and the product itself (Baum et al., 2019). Our study directly addresses the critical need for a deeper understanding of the role of influencers and opinion leaders in driving sales and facilitating the diffusion of new products (Chatterjee, 2011; Wang et al., 2023). By empirically investigating the characteristics and behaviours of influencers within their social networks, this research enriches the existing literature by elucidating how these factors contribute to brand growth during new product launches.

6.3. Managerial implications

From a managerial viewpoint, the findings of this research have important implications for companies seeking to leverage influencer marketing as part of their brand strategy. By identifying the influencer behaviours and characteristics that effectively transfer followers to the brand, this study can assist companies in selecting the most suitable influencers for their campaigns expanding their brand's social network. The research highlights the importance of influencers who interact substantially with their followers, as their behaviour and characteristics play a crucial role in driving user engagement and fostering brand growth. Moreover, this study offers valuable guidance to the influencers themselves. By understanding the factors that attract their followers' attention to a particular brand, influencers can tailor their behaviour to optimize their impact. Influencers can leverage the insights gleaned from this research to fine-tune their brand promotion strategies and increase user engagement. Here are actionable steps derived from the study:

- Frequent Interactions: Interact actively with followers by promptly responding to comments, initiating meaningful conversations, and encouraging interactions such as likes and retweets. This fosters a sense of connection, amplifies user attention, and ignites interest in both the influencer's content and associated brands. Maintaining frequent interactions can help influencers build a loyal and engaged follower base, thereby amplifying their influence and impact within their network.
- Strategic Network Positioning: Strengthen centrality within social networks by expanding connections and nurturing genuine relationships with a substantial follower base. Cultivating authentic connections fosters increased user participation and deepens interest in the influencer's content and brands. A strong network centrality not only facilitates the dissemination of brand-related content but also enhances the perceived credibility and authority of the influencer, thereby attracting new followers to the brand.
- Boosting Influencer Popularity through Enhanced Post Popularity: Implement strategies to boost the visibility and popularity of posts. This includes optimizing content quality and utilizing strategic timing techniques. By increasing post popularity, influencers can attract more attention to their content, expand their audience reach, and enhance their overall popularity and effectiveness in promoting brands.

To further enhance the practical value of this study, we recommend specific criteria for companies to consider when evaluating potential influencer partnerships. Particularly, when selecting influencers, companies should evaluate their network positioning and centrality, employing metrics, such as DC, to quantify the influencer's connections within his/her network. This approach enables companies to pinpoint influencers with substantial sway within their social networks. Additionally, companies need to evaluate influencers' interaction frequency, to determine how often influencers interact with their followers through comments, shares, and other forms of interactions. Such interactions not only foster deeper emotional connections but also significantly enhance follower loyalty. Finally, companies should gauge influencer popularity by analysing the volume of likes received by his/her posts. This metric serves as a critical indicator of the influencer's resonance with the target audience and his/her ability to drive follower transfer to the brand.

Overall, this research can serve as a practical resource for both companies and influencers in the realm of influencer marketing. It provides actionable insights that can inform decision-making processes, allowing companies to make informed choices when selecting and formalizing agreements with influencers. At the same time, it empowers influencers to effectively promote brands and direct their followers' attention toward the sponsored brand. By aligning influencer behaviour with user preferences and brand goals, companies can maximize the value derived from influencer collaborations and effectively drive the growth of their social networks, which in turn may yield higher profitability in the long run.

6.4. Limitations and future research

Our research comes with some limitations that pave the way for future research directions. First, the definition of RFT within our study focuses solely on users acquired by the brand through the influencer's network, thereby excluding those who started following the brand due to the influencer's viral posts without being followers of the influencer. Second, our study encountered limitations in the dataset size, particularly in the number of influencers observed. This constraint arose from the challenges in the data collection process, including restrictions imposed by Twitter on downloading large datasets. The exclusive reliance on Twitter data also overlooked potential insights from other influential platforms like Instagram, YouTube, and TikTok. To address these limitations, future research endeavours should adopt a comprehensive approach to data collection, incorporating multiple social media platforms. By diversifying the data sources and expanding the breadth and diversity of our dataset, future research can strengthen the robustness and generalizability of the results. Third, exploring further dimensions of influencer behaviour and characteristics that could influence brand social network growth within the gaming context could be of significant interest. These dimensions might encompass authenticity and transparency in influencers' interactions with their audience, including practices such as disclosing sponsored content or sharing personal anecdotes. Other factors worth examining include publication strategies, such as the timing and frequency of posts, and collaborations with other gamers, brands, or influencers. By analysing these aspects, we can deepen our understanding of the interactions between influencers, users, and brands within the gaming landscape. Finally, replicating our study in various settings would allow us to validate and extend our findings. Such an approach would provide a more comprehensive understanding of how influencer behaviour and characteristics impact brand growth across diverse contexts. By examining different settings, we can identify whether certain behaviours or characteristics hold greater prominence in specific contexts, shedding light on their varying impact. For instance, behaviours proving highly effective in one industry may have less relevance in another, highlighting the importance of context-specific strategies. Conversely, this approach may unveil additional relevant behaviours or characteristics previously unnoticed, enriching our understanding of influencer dynamics. This granular insight paves the way for the development of highly targeted influencer marketing strategies, fine-tuned to resonate with diverse audience demographics and industry landscapes.

CRediT authorship contribution statement

Elisabetta Benevento: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Davide Aloini:** Writing – review & editing, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Paolo Roma:** Writing – review & editing, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Davide Bellino:** Software, Formal analysis, Data curation.

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.

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