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Measuring Social Influence in Online Social Networks - Focused Literature Review on Human Behaviors

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ABSTRACT

The prominence of social influence (SI) in online social networks (OSNs) has grown exponentially, impacting diverse sectors such as marketing, political campaigns, public health, and societal culture. As OSNs continue to shape behaviors and interactions on a global scale, the need for a comprehensive understanding of SI and associated measures becomes critical. While existing measures primarily focus on network structures or graphical theories, behavioral investigations remain narrowly scoped. This study addresses this gap through an extensive focused literature review, analyzing 88 academic studies that provide deeper insights into human behaviors. From this analysis, twelve key human behavioral factors essential to understanding and measuring SI were identified, grounded in established sociological and psychological theories. The study further highlights challenges in current methodologies and proposes directions for future empirical validation. By adopting a behavioral perspective, this research offers actionable insights for academics and industries seeking to leverage SI, paving the way for more nuanced and effective measurement models in OSNs.

Keywords: *Social influence theories, Social influence measurements, Social influence behavioral theories, Literature review, Social influence models, Online social networks, Human behavior theories*

INTRODUCTION

Social Influence (SI), as defined by the American Psychological Association, refers to changes in an individual's feelings, thoughts, or behaviors caused by the real, perceived, imagined, or suggested presence of others (Chaudhry & Irshad, 2013). Any alteration in a person's behavior, mood, or thought, influenced by others or groups—even if imagined, predicted, or suggested—constitutes influence, declares Burt (1987). Influencers, with their intrinsic ability to sway thoughts and behaviors, play a pivotal role in society, potentially sparking significant social revolutions (Gladwell, 2000). The rise of Online Social Networks (OSNs) has amplified their influence, providing digital platforms for social interaction, community building, and information dissemination to over 5.17B users globally as of July 2024 (Dean, 2024). These platforms allow users to form communities, share ideas, create digital content, and disseminate information (Yu et al., 2010). Platforms like Facebook, Twitter (X), and Instagram have transformed how social dynamics operate by enabling global connections and accelerating the spread of influence (Smith & Taylor, 2017). Within OSNs, SI plays a critical role in decision-making processes, with its impact shaped by personality traits, psychological states, and demographics (Pratkanis, 2011). Additionally, mechanisms like information cascades and echo chambers contribute to the spread and reinforcement of viewpoints (Cinelli et al., 2021). Consequently, OSNs have evolved into powerful instruments for distributing SI, significantly shaping social norms, opinions, and behaviors worldwide (Goyal et al., 2013). Identifying key influencers within these networks becomes particularly crucial, as their ability to catalyze change can influence the social direction of communities and organizations (Gladwell, 2000). By recognizing the influencers, societies and organizations guide and manage SI, capitalizing on the interconnected nature of today's world (Rogers & Cartano, 1962).

The marketing domain has undeniably taken center stage, benefiting on the vast opportunities presented by SI in OSN. By leveraging SI strategies, marketers have significantly influenced consumer purchasing decisions (Sridhar & Srinivasan, 2012). Influencer endorsements on platforms like Instagram have been particularly impactful, driving consumer behavior and resulting in substantial sales spikes (Mulcahy et al., 2024). Brands harness SI to stay relevant and maintain a competitive advantage in the evolving digital marketing landscape (Hafez, 2022). SI's influence extends far beyond marketing, reshaping industries and driving innovation across diverse domains. During the COVID-19 pandemic, SI played a pivotal role in shaping public discussions on critical issues such as immunization and social distancing (Lipsev & Losee, 2023). Research has linked SI to better medication adherence, higher physical activity, improved diet, and reduced tobacco and alcohol use (Christakis & Fowler, 2007). Similarly, SI is known to exhibit a spontaneous on-off disposition in digital environments (Simon et al., 1998), triggering heightened interest in contagion studies (Loersch et al., 2008). Social groups can exhibit collective intelligence when averaged judgments contrast with individual judgments, often swayed by expert opinions (Dong & Pentland, 2007). SI also pervades cultural markets, influencing the adoption of scientific and technological advancements, and disseminating social practices, including economic influences, stimulating financial turbulence (Avery & Zemsky, 1998). In the educational sphere, the digital era has brought new dimensions to SI, with social media and online communities becoming central platforms for collaborative learning and information exchange (Greenhow et al., 2009). Moreover, societal culture is continually reshaped and transformed by the dynamics of SI (Hofstede, 2011).

Despite the prominence, it can be argued that there is a lack of a systematic and reliable model to measure SI in OSN. Understanding SI has piqued the curiosity of researchers and psychologists since the first recorded attempt by the Sophists¹ to the current modern research by Robert Cialdini² (2001). The power of influence has been long studied (Travers & Milgram, 1967) and, more importantly, how its orchestration in society is progressively gaining attention (Kapoor et al., 2018). These academic research studies have sought to characterize human influencing behaviors in concrete measurements through network properties, graphical measures; nonetheless, the results have been fragmented. Only a few researchers have attempted to depict the human behavior-influencing qualities in a network architecturally, but these efforts have neither been thorough nor grounded in established psychological theories. Lee et al. (2011), argued for an alternative theory focusing on informational SI and concluded through their experimentation that it played a moderating role rather than the anticipated direct role in consumer behavior. Similarly, while several

¹ Sophists - A sophist was a teacher in ancient Greece in the fifth and fourth centuries BC.

² Robert Cialdini - Renowned scientist and author of the best-selling book, "The Influence"

commercial product startups, like Klout³, Brandwatch⁴ and Kred⁵, strive to discover and engage with influencers to benchmark their social media impact, none have created a comprehensive measure.

This study will address this gap by examining the many measurements, and techniques used to assess SI, focusing on human behavior traits and their representation in OSN. To that purpose, the study particularly seeks to answer the following research questions:

RQ1: What are the critical human behavior theories that play a role in understanding the influence behavior of social media users?

RQ2: How do human behavior theories manifest in measuring SI in OSN? What are the comprehensive approaches, metrics, and methods prevalent in existing studies?

RQ3: Are psychological theories represented adequately in measuring SI in OSN, and do this scale across multiple dimensions of OSN?

By examining the academic literatures in the area through these research questions, this study offers an encyclopedic assertion of the subject, and approaches, to guide research and improve future studies in this field. It explicitly focuses on cataloging through the psychology and behavior theories and adds exhaustive reference knowledge to the discipline. The remainder of this paper is organized to ensure a logical flow for readers' comprehension. We begin by establishing the significance and scope of the research, followed by an overview of the methodology. Next, we delve into the literature synthesis analyzing human behavior-based characteristics through the lens of twelve psychological theories. We also address the challenges and limitations present in current studies, using practical examples, and propose potential approaches and directions for future research. Finally, the concluding section provides a concise summary of the study's key findings.

MOTIVATION - SIGNIFICANCE OF RESEARCH

The profound impact of SI in OSN reshapes how individuals connect, share, and make decisions (Guadagno & Cialdini, 2010). Understanding the dynamics of SI within these digital environments is critical, as they directly affect how people engage with brands, respond to influencer marketing, make health-related choices, navigate economic shifts, adapt their learning experiences, and shape their cultural perspectives. The ripple effects of SI extend beyond individual decision-making, influencing collective behaviors, driving trends, and shaping societal norms (Anagnostopoulos et al., 2008). Given the rapid information exchange and the power of digital communities to amplify voices, exploring the mechanisms of SI is essential for comprehending its broader social implications.

Marketing: As outlined in the State of Influencer Marketing (2024), the influencer marketing industry has exploded into a formidable \$24B sector. Incorporating a robust measure of SI in marketing strategies confers multifaceted benefits, enhancing the precision and efficacy of promotional efforts. Identification and collaboration with influencers, as a central component enable marketers to target specific demographics with unprecedented accuracy (Brown & Hayes, 2008). Market researchers have been working to develop a framework to guide businesses in selecting the most suitable influencers (Vrontis et al., 2021), a task made increasingly complex by the emergence of virtual influencers (Huang, 2023). Simultaneously, consumers themselves are evolving into brand ambassadors (Gensler et al., 2013). Moreover, the cost-effectiveness of influencer collaborations, coupled with their potential to foster engaged communities, positions this approach as a strategic alternative to traditional advertising channels (Jin et al., 2019). By aligning marketing efforts with trending topics and influencers, brands can harness the power of SI to maintain relevance and gain a competitive advantage in the ever-evolving digital marketing landscape. This strategic integration optimizes current campaigns and positions brands to anticipate and capitalize on emerging opportunities within the digital realm.

³ Klout – Klout was a score platform to help identify an individual's social influence score. It was shut down in 2018.

⁴ Brandwatch – Brandwatch acquired PeerIndex, a web technology company that enables users learn about the influence on social media platforms.

⁵ Kred - Kred is a score and a platform for increasing social media user online influence.

World Economics: The interconnectedness facilitated by OSNs and the dissemination of information through these platforms profoundly impacts global economic dynamics. Research by Acemoglu et al. (2001) emphasizes the role of institutions in economic development, indicating that social and political structures significantly influence economic outcomes. OSNs catalyze trends in the digital age, affecting consumer preferences and market demands (Smith & Brynjolfsson, 2001). Additionally, the concept of social proof, as explored by Cialdini (2001), elucidates how individuals often make economic decisions based on the actions and choices of others, amplifying the ripple effect of SI in economic transactions. Understanding these dynamics is crucial for policymakers, businesses, and economists, as it enables a more comprehensive analysis of economic phenomena within the contemporary social context.

Citizen Healthcare: SI plays a significant role in citizen healthcare, affecting health-related decisions, behaviors, and perceptions. Research by Christakis and Fowler (2007) highlights the impact of OSNs on health behaviors, suggesting that individuals are influenced not only by their own choices but also by the health-related choices of those within their social circles. Social support and influence can positively contribute to health outcomes (Umberson & Montez, 2010). Moreover, the diffusion of health information through OSNs has become a prominent factor influencing public perceptions and behaviors regarding healthcare practices (Moorhead et al., 2013). Understanding the dynamics of SI in citizen healthcare is crucial for healthcare professionals and policymakers, as it can inform targeted interventions and public health campaigns to leverage positive influence for improved health outcomes.

Global Politics & Diplomacy: SI is climactic in global and policy diplomacy, shaping international relations and decision-making processes. Research by Keohane and Nye (1987) on soft power emphasizes the significance of cultural and ideological influence in diplomatic interactions. In the contemporary era, digital diplomacy leverages social media as a tool for public diplomacy, allowing nations to project soft power and influence global perceptions (Seib, 2012). The concept of public diplomacy, as explored by Fisher (2011), underscores the role of SI in diplomatic practices, emphasizing the importance of interpersonal relationships in shaping international cooperation. Understanding SI dynamics in global diplomacy is essential for policymakers and diplomats to navigate the complexities of international relations and promote effective diplomatic strategies that resonate with diverse global audiences.

Societal Culture: SI is a cornerstone in the evolution of societal culture, shaping norms, values, and behaviors. Societal culture is a complex interplay of shared beliefs, customs, and traditions influenced by social interactions. The work of Hofstede (2011) highlights the impact of societal values on cultural dimensions, emphasizing how SI contributes to the formation of collective cultural traits. Furthermore, the social identity theory by Tajfel and Turner (1986) elucidates how individuals categorize themselves and others into social groups, influencing cultural dynamics through intergroup relations. In the digital age, OSNs contribute significantly to disseminating cultural trends, reflecting the power of SI in shaping societal norms (Boyd & Ellison, 2007). Qin et al. (2011) explore the determinants of user acceptance of OSNs, focusing on the role of SI. The findings reveal that both the subjective norm and critical mass significantly impact perceived usefulness, influencing users' intention to use the networks. Understanding the nuances of SI in societal culture is crucial for sociologists, anthropologists, and cultural theorists, as it unveils the mechanisms through which cultures evolve and adapt over time.

Education & Literacy: SI plays a crucial role in education and literacy, shaping learning environments and educational outcomes. The digital era has brought forth new dimensions of SI in education, with social media and online communities serving as platforms for collaborative learning and information dissemination (Greenhow et al., 2009). Nguyen et al. (2024) asserted that SI positively impacts students' intentions to use communication technologies for learning, with this effect being enhanced by daily social media use, highlighting the role of OSN in education. Understanding the dynamics of SI in education is vital for educators, policymakers, and researchers, as it informs instructional strategies, curriculum development, and literacy initiatives that harness the power of social interactions to enhance educational experiences.

The intricate web of OSNs encompasses various facets, including commercial economics, social welfare, evolving social trends, generational perspectives, shifts in the political landscape, and numerous other dimensions. Individuals equipped with insights into the mechanisms of SI can refine their behaviors and employ influence tactics more adeptly, increasing the likelihood of achieving their desired outcomes.

RELATED WORK – ZOOMING IN ON THE SCOPE DEFINITION

The current state of the union on research studies are heavily focused on understanding SI in OSN through the inherent graph and network theories of OSN. The significant problem of finding the most influential entities within the network has been resolved using gradient-based optimization techniques (More & Lingam, 2019). Samantha et al. (2021) measured SI by incorporating fuzzy systems to derive mathematical formulations that represent influence of a node within the social networks. Influence propagation using models was established using probabilistic models to understand the influence from a knowledge-sharing network (Richardson & Domingos, 2002) within OSN. Baabcha et al. (2022) identify influential nodes using influence diffusion and maximization techniques. Studies have also taken advantage of the latest technology revolution with big data and machine learning to understand the intricacies of SI in OSN. Bonchi (2011) adopted a data mining perspective to identify influence propagators in OSN while clearly acknowledging the shortcomings of the study. Bhat et al. (2020) used hybrid ranking algorithm to identify the influencer nodes within the network and Popescu et al. (2016) coupled ranking with multiple linear regression to interpret the influence of social media on student learning.

Commercial platforms like Klout, Kred, and Brandwatch initially gained significant attention; however, they struggled to differentiate between social enthusiasts engaging purely to boost their influence scores and genuine social media users with authentic engagement. Commercial analytical tools attempt to compute influence by reducing it to fit into a single number, relying on its simplest form without comprehending the complexities in human behavior characteristics (Anger & Kittl, 2011). Based on user contact network structure and traffic tweets (posts), each commercial application employs a distinct methodology to determine the impact (Del Campo-A´vila et al., 2013). Klout was one of the most well-known commercial products (Rao et al., 2015) that became popular given their ability to provide an influence score to a social media user, however, folded with the same lightning speed in which it grew to be a unique problem solver (Hollister, 2018). These commercial tools settled on a model to measure influence without adequate theoretical background to substantiate the human behaviors. For instance, Klout prioritized authority, whereas Kred prioritized engagement (Mei et al., 2015) as key indicators for SI, but do not bear any evidence of theoretical proof. Danisch et al. (2014) found the discrepancy with the Klout score and inserted a counter to include the social capital of an individual to define a better measure. This was still inadequate as it did not capture the full spectrum of human emotions that contribute to SI.

Even the studies focused on human behaviors limited to a few characteristics. For instance, Li et al. (2015) focused on relationships and conformity to measure SI. Lorenz et al. (2011) focused on the conformity ignited by the crowd behavior. Wiedmann and von Mettenheim (2021) demonstrated that success criteria were more strongly associated with influencers than with the information in their profiles, highlighting the essential role of credibility. Danisch et al. (2014) investigated the organizational structure of social capitalists and the extent of their connections within the Twitter (X) follower-followee network, revealing their prominent presence attributed to their unique roles. Shi et al. (2017) considered the evolution of user interests throughout the progression of an event and identified that user interests significantly enhanced the ability to discern a user’s impact through changes in shared interests. Qin et al. (2011) explore the effects of SI on user acceptance understanding subjective norm and critical mass.

Cialdini (2005) identifies a powerful form of influence at three key and frequently encountered decision-making stages: first, when individuals act as observers and determine the reasons behind their own behaviors; second, when they function as strategists and decide how to affect the actions of others; and third, when they serve as experts and choose whether to seek input from others. He has done several research on the prominence of influence. His research in partnership with Goldstein (Cialdini & Goldstein, 2004) focuses on compliance and conformity and in another subsequent paper emphasize social norm (Goldstein & Cialdini, 2011). Guadagno and Cialdini (2010) assert that individuals are generally consistent with their attitudes and behaviors. In his seminal work ‘Influence’, he presents six key principles, however, through the lens of persuasion (Cialdini, 2001). This wisdom inspired us to retrospect influence based on sociological and psychological theories.

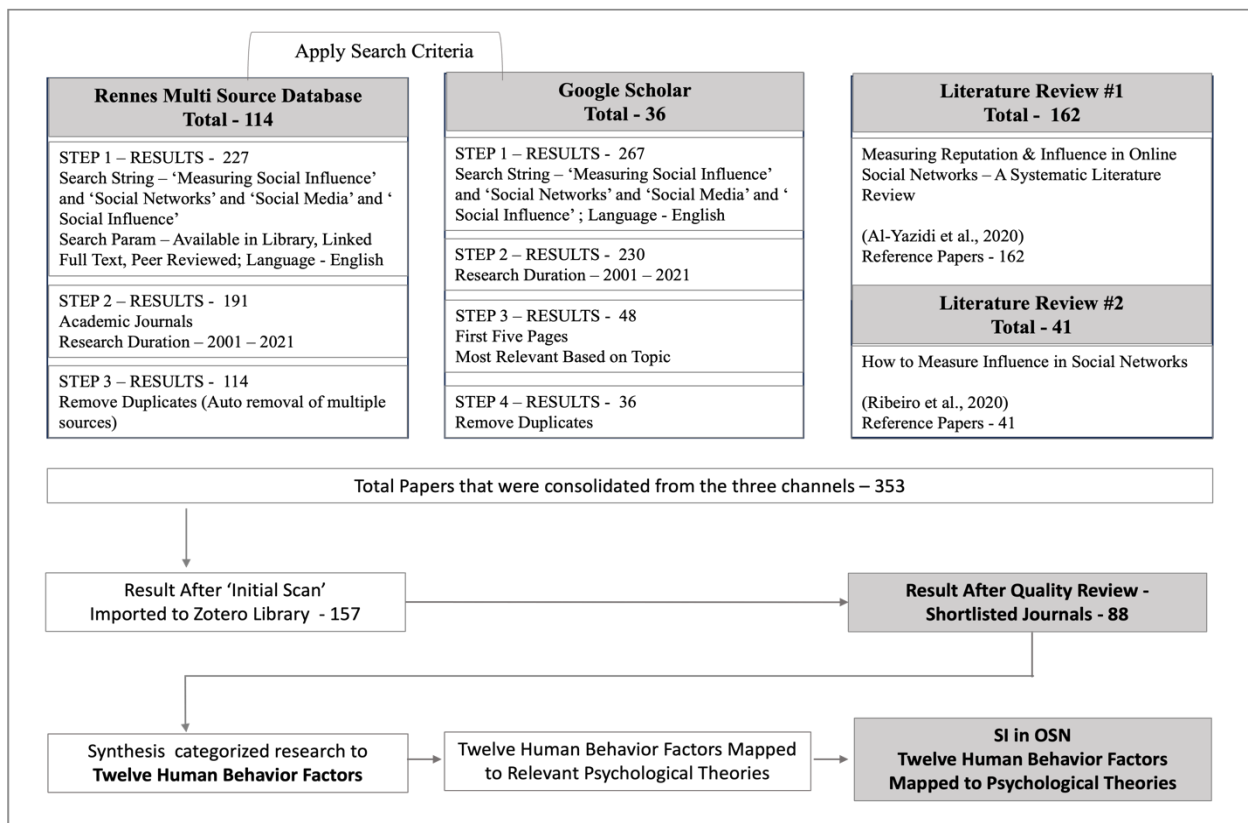
While most of the studies often use graph theories, statistical models, and algorithms to analyze SI in OSNs, they overlook the complexity of human behavior, leading to biased predictions. Cialdini’s work, though highly regarded in marketing and behavioral science, focuses on short-term persuasion aspect of influence governed through principles like reciprocity and social proof. In contrast, influence is a broader, long-term process shaped by ongoing

social interactions, group dynamics, and dynamics of OSN. To accurately measure SI in OSNs, a more holistic understanding of human behavior is essential.

METHODOLOGY

The literature review aims to achieve the specific objective of identifying human behaviors critical to understanding and measuring SI in OSNs. Systematic literature reviews (SLRs) synthesize scientific evidence to address specific research questions through a transparent and reproducible process. They aim to include all relevant published evidence on the topic while critically evaluating the quality of this evidence. Key features include exhaustive searches, explicit inclusion and exclusion criteria, and a comprehensive synthesis of findings, often covering diverse methodologies and perspectives (Lame, 2019). While we adopted the structured rigor of an SLR, we narrowed the scope to conduct a focused review targeting the human behavior characteristics of SI in OSNs. This approach prioritized depth over breadth, emphasizing selective inclusion of literature to address a precise research question and objective. Unlike an SLR, it allowed for greater methodological flexibility, incorporating iterative refinements as insights emerged (Huelin et al., 2015). By adopting this methodology, we were able to explore relevant studies with a targeted lens, emphasizing contextual relevance and theoretical grounding over exhaustive breadth. As outlined in Figure 1, a structured and rigorous process was followed to ensure a thorough exploration of practical and critical issues related to SI in OSN. The focus was on evidence-based research grounded in strong theoretical frameworks, while also incorporating relevant observational studies, reports, and conference papers.

Figure 1 - Focused Literature Review



The search terms were derived from the research questions exploring the measure of SI based on human behaviors in the OSN. An initial exploratory search in the *Rennes Multi-Source Database* focused on SI in behavior theories in OSNs. The keywords shortlisted were ‘social influence measurements’ and ‘social influence in online social networks’

and ‘human behaviors in social influence’ and ‘social influence in social media’. A total of 227 records were identified. The inclusion criteria for the search were linked full text, peer-reviewed studies in academic publications, English language, and year of publication after 2000 to focus on the current SI research. After removal of duplicates the search resulted in 114 publications. The investigation was extended to *Google Scholar* with similar search parameters (first five pages each) and 36 publications were identified. 162 key references from ‘Measuring Reputation and Influence in Online Social Networks: A Systematic Literature Review’ (Al-Yazidi et al., 2020) and 41 key references from ‘How to Measure Influence in Social Networks’ (Ribeiro et al., 2020) were incorporated to enrich the analysis, contributing to a total of 353 journal articles included in the study. Post the initial scan of review of title, and abstracts, introduction & conclusions in a few cases, 157 relevant literatures from the search strategy were shortlisted that would be suitable for further analysis and reporting.

Two sets of criteria were used to narrow the search further to validate the quality of the journals. The first set was focused on structural and qualitative components like:

QA1: Does the literature reflect the setting in which the study was conducted?

QA2: Is the study approach and research methodology thoroughly described within the literature?

QA3: Does the article correctly describe the data-collecting procedures and data analysis approach?

The second set concentrated on the relevance of the information and included:

QA4: How does the study evaluate influence based on human behavior representation in OSN?

QA5: Does the research paper relate to the research context from psychological theories?

The authors convened regularly to review the 157 shortlisted articles, following established guidelines detailed above to assess whether each study aligned with the premise of the research. This review process evaluated the methodology, data collection, and overall rigor of the studies, with an emphasis on relevance to understanding human behaviors related to influence resulting in a final set of 88 relevant literatures (Appendix 1 shows the included literature). Zotero⁶ served as the official record system for collecting the picked journals and the accompanying metadata, such as Item Type, Title, Authors, Abstract, Publication Year, Volume, Date, ISSN, Library Catalog, and Publisher.

Any literature review begins with data extraction and ends with synthesis to gain a meaningful conclusion. The research began by defining the scope, establishing clear criteria for selecting behaviors to ensure alignment with the research objectives. Behaviors were then categorized based on common themes, contexts, and relevance, resulting in the identification of twelve distinct human behaviors. These behaviors were subsequently linked to established psychological theories using a structured methodology:

- **Behavioral Characteristics Analysis:** Each behavior was examined in depth to uncover its underlying motivations, cognitive processes, emotional dynamics, and social contexts.
- **Theory Selection:** A thorough review of psychological theories was conducted to pinpoint theories that best aligned with the traits and nuances of each behavior.
- **Mapping Behaviors to Theories:** A systematic approach was developed to map behaviors to corresponding theories, focusing on identifying the psychological theory that directly explained the behavior and ensuring its contextual alignment for added depth.

With this approach, the human behavior factor was aligned to a relevant psychological theory allowing for a nuanced examination of the SI through a theoretical perspective. Table 1 summarizes the 88 papers grouped under the human influence factors and the corresponding psychological theory that it has been mapped into.

⁶Zotero is a free and open-source reference management software.

Table 1 – Journals Grouped Under Human Behaviors & Theories

Factor #	Influence Factors (# of Journals)	Literature References / Studies	Theory
1	Common Interest (5)	Ji et al. (2015); Bilal (2021); Bergin (2016); Shi et al. (2017); Zhou et al. (2018)	Social Identity Theory Tajfel and Turner (1986)
2	Relationships (9)	McPherson et al. (2001); De Choudhury et al.(2010); Peng et al. (2017); Anagnostopoulos et al. (2008); Cataldi et al. (2013) ; Ma et al. (2017); Smailovic et al. (2018); Shi et al. (2014); Romero et al. (2011)	Social Exchange Theory Cook and Emerson (1987)
3	Social Capital (8)	Julien (2015); Badawi et al. (2019); Subbian et al. (2014); Ram and RizoIU (2021); Bakshy et al. (2011); Horng et al. (2020); Dugue et al. (2015); Danisch et al. (2014)	Social Capital Theory Bourdieu (2011)
4	Social Contagion (7)	Christakis and Fowler(2013); Liang (2021); Ferrara and Yang (2015); Jung and Neusch (2019); Herrera et al. (2015); Cinelli et al. (2021); Kwon et al. (2014)	Social Contagion Theory Gustava LeBon - reviewed by Bosanquet (1899)
5	Shared Sentiments (6)	Bae and Lee (2012) ; Wu and Ren (2011) Arora et al. (2019); Sun and Ng (2014); Servi et al. (2014); Stieglitz and Dang-Xuan (2013)	Emotions as social information - EASI theory van Kleef (2009)
6	Social Conformation (8)	Book and Tanford (2020); Li and Wu (2018); Muchnik et al. (2013); Lorenz et al. (2011); Cialdini and Goldstein (2004); Goldstein and Cialdini (2007); Li et al. (2011); Li et al. (2015)	Conformity Theory Deutsch and Gerard (1955)
7	Personal Brand (4)	Faliagka et al. (2018); Yamaguchi et al. (2020); Zacharopoulos and Rigou (2021); Siedman (2013)	Self Presentation Theory Goffman (1949)
8	Likability (9)	Guadagno et al. (2013); Taillon et al. (2020); Mei et al. (2015); Li and Yin (2018); Qasem et al. (2017); Chekima et al. (2020); Hong et al. (2019); Myers (2021); Beterburg and Bartels (2017)	Source Attractiveness Model McGuire (1985)
9	Dynamic Social Impact (4)	Oc and Bashshur (2013); Miller and Brunner (2008); DiFonzo et al. (2011); Bullock (2007)	Dynamic Social Impact Theory Latane (1996)
10	Expertise (12)	Zhao et al. (2016); Hall and Blanton (2009); Askarisichani et al. (2020); van der Valk (2017); Alp and Oguducu's (2018); Fang et al. (2014); Kong and Feng (2011); Weng et al. (2010); Liu et al (2012); Hamzehei et al. (2017); Tang et al. (2009); Zhaoyun et al. (2013)	Expertise Theory Goodall (2016)
11	Opinion Leader (8)	Bergsma et al. (2014); Oro et al. (2017); Afridiana et al. (2019); Zhao et al. (2018); Ma and Liu (2014); Bodendorf and Kaiser (2009); Van Eck et al. (2011); Farivar et al. (2021)	Two Step Flow Communication Theory Katz and Lazarsfeld (1959).
12	Credibility (8)	David Huffaker (2010); Abu-Salih et al. (2020); Alrubaian et al. (2017); Khrabrov and Cybenko (2010); Scheinbaum and Wang (2018); Wiedmann and Von Mettenheim (2021); Wijesekara and Ganegoda, (2020); Hu et al. (2019)	Source Credibility Theory Hovland and Weiss (1951).

LITERATURE REVIEW SYNTHESIS

The literature review synthesis presents key findings from the 88 shortlisted research articles, categorized under twelve SI factors linked to established psychological theories. This structured approach as shown in Figure 2, provides a comprehensive view of how these behaviors shape and influence interactions within OSNs. By summarizing these critical factors, the review offers clarity on how SI manifests and functions, laying a strong foundation for further analysis and exploration.

Figure 2 – Social Influence in Online Social Networks: Human Behaviors as Key Influence Factors



Common Interests as an Influence Factor

In an age of information overload, filtering based on common interests will assist people in inferring the information they are ultimately interested in. Ji et al. (2015) investigated the role of social media users' interests in online trust formation, confirming that the rapid accumulation of common interests leads to trust in relationships which then creates influence. It finds that common interests increase significantly before trust is established and continue growing afterward. Users with similar tastes are more likely to form trust-based relationships, with common interest peaking around the time trust is created with ongoing user activity influencing the effect of taste similarity, shedding light on social relations in online networks. By combining lexical and sentiment analysis with domain-based content analysis, Bilal (2021) assessed a social media user's influence potential based on shared content interests. This research investigates the impact of friends and followers on the perceived helpfulness of reviews by utilizing social network features. Passionate affinity groups are communities where individuals with shared interests gather, frequently online, to create, critique, analyze, and collaborate. Typically, members join these groups already possessing a strong interest in the subject matter and engaging in social interactions on dedicated websites within these communities enables participants to develop both new and well-established personal interests (Bergin, 2016). Another exciting perspective from Shi et al. (2017) accounted for changes in user interests as an event progress. Their HEE (Hot Event Evolution), a user-interest-based event evaluation model, dramatically improved the identification of the influence exerted by the user based on changes to common interests. Zhou et al. (2018) introduced DSUN (Dynamic User Networking Model), which accommodates a similarity-based representation of implicit ties based on topic-aware traits and an influence-

based representation of explicit relationships based on behaviors. This research measures common interests by topological features such as overlap rates, taste similarity, and user degree ranking.

Given the significant role of common interests in creating SI, we examined Social Identity Theory (Tajfel & Turner, 1986) to better understand this phenomenon within OSNs. Social Identity Theory posits that a group consists of individuals who perceive themselves as members of the same social category and share common interests. In OSNs, these shared common interests facilitate the formation of distinct social identities as users gather in virtual communities centered around everyday topics. This internalization emphasizes intragroup similarities and intergroup differences, fostering a sense of belonging and loyalty that enhances SI. OSN features such as groups, forums, and hashtags amplify this process by promoting visibility and interaction among members. As a result, group norms are reinforced, information dissemination aligns with group interests, and trust among members facilitates effective influence. By leveraging Social Identity Theory, the research can elucidate how shared interests within OSNs create robust social identities that drive influential user behaviors and interactions.

Relationships as an Influence Factor

As Carnegie⁷ says, “If authentic leadership is about influence, then the influence is about relationships, and relationships are about the investments made into people.” Social relationships in online communities are formed when members join the group, knowing one or a few members. The homophily principle states that similarity fosters connections in relationships like friendship, work, and support, making personal networks largely uniform in characteristics such as race, age, and education. This similarity limits the diversity of information and interactions individuals receive, and fosters relationships within the group (McPherson et al., 2001). De Choudhury et al. (2010) explores how the tendency for similar individuals to connect impacts the diffusion of information on social media. By analyzing diffusion characteristics across various user attributes (e.g., location, activity), the study finds that accounting for these attributes can improve predictions of information diffusion by 15-25%, highlighting their significant role in explaining actual diffusion patterns and external trends. Peng et al. (2017) develop a social relationship graph, providing a robust foundation for understanding SI. Additionally, they introduce an evaluation model that measures both direct and indirect influence by incorporating friend entropy and interaction frequency entropy, which capture the complexity and uncertainty inherent in SI in OSN. Once social media users become part of a group, they organically become subjected to the influence of ideas and thoughts shared within the group.

The study by Anagnostopoulos et al. (2008) focuses on understanding and comprehending SI in OSN through two factors of relationship: Homophily and Confounding. The paper examines how social ties in online systems impact user behavior and tackles the challenge of distinguishing SI from other factors like homophily. The authors propose two tests to separate SI from social correlation. Simulations on Flickr data reveal that while social correlation exists in behaviors like tagging, it cannot be solely attributed to SI. Cataldi et al. (2013) focused on tracking changes in user relationships based on the topic of conversations. In their study, they use an N-gram model classification strategy to categorize the information into domains to estimate a user’s influence on a community within the domain. Using case studies from Twitter (X), their research demonstrates the validity of this approach in understanding information diffusion and user influence across different domains. On a relative note, the MapMe algorithm from Ma et al. (2017) uses the Doc2vec technique to calculate user relationship similarity based on the user’s ego network properties integrated with the user profile. Their approach of using the organic nature of OSN ego networks combined with user profile outperforms the existing methods with 10% on average accuracy in detecting relationships. The study by Smailovic et al. (2018) estimates an influencer’s social impact by the user’s placement in the social network and their relationships with fellow users. Given getting complete user data from OSN is often a complex or impossible tasks, the authors propose an alternate to evaluate algorithms that calculate SI using limited data, focusing on accuracy and precision. Building on traditional approaches from statistics and machine learning, the methodology is demonstrated through a case study with four different algorithms, identifying the most accurate methods for predicting SI. Shi et al. (2014) present the statistical associations between user characteristics found in social networks and retweeting habits. With their two-stage consumption-sharing model, they demonstrate that unidirectional weak relationships are more

⁷ Dale Carnegie (November 24, 1888 – November 1, 1955) was an American writer and lecturer

likely to participate in exchanging social content. Romero et al. (2011) offered an all-encompassing model of influence based on the notion of inactivity or passiveness in a social network. This paper introduces a novel influence measure on Twitter (X) that incorporates both network structure and user passivity. The algorithm considers the influenced audience's size and passivity, distinguishing it from traditional measures that rely only on topical metrics like follower count or retweets.

Investigating Social Exchange Theory in the context of SI within OSNs is crucial because it provides a comprehensive lens for understanding core aspects of social relationships and their interactions, such as power, dependence, reciprocity, and social cohesion (Cook & Emerson, 1987). By examining these interactions through the lens of Social Exchange Theory, we gain insights into how individual behaviors are shaped by the expectations of reciprocity and mutual benefit, which are central to how SI operates. This understanding is essential to reveal how influence flows through networks, how alliances and social bonds strengthen or weaken over time, and how individuals' roles and relationships drive individual and collective actions within OSNs. In essence, relationships and exchange are central to understanding how ideas, behaviors, and trends propagate, making them a crucial focus for any investigation into SI in digital environments. A deeper exploration of these concepts in OSNs will enable a more accurate and nuanced measurement of SI, reflecting the complexities and bidirectional nature of relationship interactions, ultimately leading to a clearer understanding of how influence shapes behaviors in digital communities.

Social Capital as an Influence Factor

The benefits of sociability are referred to as social capital. The human capacity to regard others in social relationships and social structures, to think and behave generously and collaboratively, is the source of social capital. Julien's (2015) summary encapsulates the main arguments and contributions highlighting the shift from American communitarianism to Bourdieu's framework on social capital and the introduction of an agonistic model for understanding online interactions and influences. A deep relationship exists between one's ability to influence and their accrued social capital. Badawi et al. (2019) research offers evidence for the significance of these relational components. Their research contributes to the literature by integrating social capital theory, examining how six social capital constructs (ability, benevolence, integrity, flexibility, information exchange, and solidarity) relate to three relationship quality constructs (trust, satisfaction, and relationship atmosphere) and how these constructs influence the effectiveness of key account management. Similarly, the study by Subbian et al. (2014) postulates that people with substantial social capital are frequently key network influencers and create a value-allocation model to compute the social capital in OSN and allocate their fair share of this capital to everyone involved in the collaboration to create a data driven generalized influence model. Ram and Rizoiu (2021) instead examine the diffusion and conductance feature through networks and the distribution of social capital. Their study introduces a generalized influence model inspired by psychosocial theories incorporating diffusion network conductance and social capital distribution. It proposes an active learning framework using human-labeled data to rank users' SI more accurately by correcting biases like over-reliance on follower count. Applying this model to COVID-19 discussions, the study finds that influential users are often executives, media figures, and military personnel rather than healthcare experts. Bakshy et al. (2011) assert that word-of-mouth diffusion can only be harnessed reliably by targeting large numbers of potential influencers, thereby capturing average effects. Their study analyzed the attributes and influence of 1.6 million Twitter (X) users by tracking 74 million diffusion events over two months in 2009. It also shows that while highly influential users may sometimes be cost-effective, ordinary influencers often offer better performance under various marketing strategies.

Hornig et al. (2020) focus on how online social capital behaviors such as bonding and bridging impact SI. They also examine how the social capital mediates the relationship with SI and explore a more detailed relationship amongst these constructs by dividing the OSN behavior into browsing and participating, social capital into bonding and bridging, and SI into receiving and giving. Social capitalists are apparent because of their specific roles, according to Dugue et al. (2015) analysis of how they are structured and how far their connections reach beyond the Twitter (X) follower-followee network. Their study finds that social capitalists hold specific roles that grant them high visibility by analyzing their position in the network's community structure and examining their behavior, organization, and influence. Additionally, it identifies limitations in existing topological measures of community roles and proposes a more flexible, unsupervised approach to understand these dynamics better. Danisch et al. (2014) took a very interesting approach. Rather than relying on the traditional way, they defined a classifier developed based on user profiles and behaviors that separates social capitalists from genuine users to balance Klout's influence score. Social Capital Theory is defined as social context features that offer productive advantages.

Given the significant role of shared interests in creating SI, we examined Social Capital Theory (Bourdieu, 2011) to better understand this phenomenon. Bourdieu (2011) defines social capital as "institutionalized relationships of mutual familiarity and recognition" accumulated over time, encompassing resources like trust and information sharing that enhance one's ability to influence others. Studies have shown that individuals with high social capital in OSNs possess greater reach and credibility, enabling them to shape opinions and disseminate information effectively. However, the psychological mechanisms behind why people are more influenced by those they have developed positive relationships with remain underexplored. Addressing this gap is crucial for fully understanding how social capital translates into effective SI in digital environments.

Social Contagion as an Influence Factor

Spontaneous transmission of traits, sentiments, or disorders within a network is organically called contagion (Levy & Nail, 1993). Since the late 19th century, social scientists have studied phenomena, albeit precise definitions have varied because most of the research on the topic was based on ambiguous or contradictory ideas. In general, social contagion is thought to be distinct from the group behavior that directly results in SI. Gustave Le Bon (Bon, 1908), a French philosopher, created the Contagion Theory in his seminal work, "The Crowd: A Study of the Popular Mind." He claimed that people behave rationally while alone but get practically hypnotized by a crowd's energy and behave emotionally and impulsively. Individuals tend to exhibit irrational and sometimes even vicious acts as they seem to lose control of their unconscious instincts (Bosanquet, 1899) and it is important to understand this phenomenon and its impact on SI.

Collective behavior is emotional and mostly irrational and results from the crowd's hypnotic influence, result in echo chambers in the OSN. Human social networks often exhibit the 'three degrees of influence' phenomenon, where the impact of an individual's behaviors, emotions, and decisions extends to their friends, their friends' friends, and even their friends' friends' friends, driving the spread of various ideas and behaviors such as obesity, smoking, cooperation, and happiness (Christakis & Fowler, 2013). Liang (2021) investigates retweeting behavior on social media, focusing on how social contagion and homophily influence information spread across different diffusion depths. Analyzing over 87,000 tweets, the findings reveal that as cascades deepen, social contagion effects—such as interaction frequency and multiple exposures—diminish, while homophily's influence increases, suggesting that the role of social contagion in information diffusion varies with cascade depth. Ferrara and Yang (2015) study on Twitter (X) explored emotional contagion by examining how exposure to positive or negative posts influences users' subsequent tweets and identified a relationship between the emotional tone of the content users encounter and the emotions they express in their own posts, highlighting varying susceptibility levels to contagion.

The study by Jung and Neusch (2019) finds that a high number of views on a YouTube video not only serves as a quality signal but also enhances the perceived suitability of discussing the video with others, independent of its content. These findings highlight how social contagion can drive the popularity and discussion of content, impacting aspiring influencers. Herrera et al. (2015) challenge the common assumption in marketing and diffusion research that social interactions remain static over time and analyze how social contagion influences adoption processes over a decade. Findings suggest that while social contagion is important for diffusion, its role in shaping adoption is less significant when social dynamics among community members are considered. The study by Cinelli et al. (2021) compares how different social media platforms influence information spreading and the formation of echo chambers. The research focuses on homophily in interaction networks and bias in information diffusion towards like-minded peers and the results indicate that users tend to cluster in homophilic groups across platforms. Social contagion caused by network exposure can boost favorability ratings of ideas or products, declared Kwon et al. (2014). Although social contagion may occur more inadvertently than direct solicitation, their findings imply that Facebook messages demonstrate the power of network exposures. Given the rapid growth of adaptation to OSN and the massive threat such contagions can cause to society, a more structural investigation of this is required to incorporate the relevance for SI measurement and, more importantly, find ways to control this human behavior tendency.

Shared Sentiments as an Influence Factor

As Dr. Simon⁸ noted, sentiments and emotions affect, distort, and sometimes entirely dictate the result of a significant number of decisions we face each day. Several studies have explored shared sentiments through multiple lenses. Human psychology dictates that anyone who wants to make the most objective judgments should learn everything about emotions and their impact on decision-making. Emotions as social information (EASI) theory states that emotional expressions shape SI by eliciting effective reactions and inferential processes in observers (van Kleef, 2009). Thus, academics are increasingly interested in how user sentiments and feelings about a subject or an issue affect influence. We propose that it is important to understand the accounting of people's innate propensity to be influenced by emotions when evaluating SI in OSN.

Bae and Lee (2012) focused on the fundamentals to prove that the influencer's sentiment may influence the followers' perception and credibility, as well as how they respond to such stimuli. This study uses sentiment analysis to assess influence by distinguishing between positive and negative sentiments expressed toward popular Twitter (X) users. The results demonstrate that the sentiments of influential users significantly impact their audience's sentiments. By applying a positive-negative influence measure, the Granger causality analysis reveals a correlation between shifts in audience sentiment and real-world sentiment about these users, providing valuable insights into how user influence operates on Twitter (X). Wu and Ren (2011) research provide insights into how sentiment spreads and interacts in online social networks. Their paper explores sentiment influence in social networks, explicitly analyzing Twitter (X) data to model both the sentimental influencing and influenced probabilities of users. The study reveals a strong correlation between users' likelihood to influence others' sentiments and their susceptibility to being influenced. Additionally, most Twitter (X) users balance influencing and being influenced sentimentally. Arora et al. (2019) focused on sentiment analysis across multiple social media networks using simple regressions and a cumulative scoring model based on engagement, outreach, sentiment, and growth attributes. As OSN is becoming a common medium for people to share information, symbols and emoticons are becoming very popular. The study emphasizes the importance of audience reactions, such as comments and replies, and incorporates overall sentiment scores to compute the influencer index. In their study, Sun and Ng (2014) aimed to assess the effect of a post's favorable or unfavorable emotion through a comprehensive vocabulary model dealing with symbols and emoticons. While it was a great start, they could not continually maintain classification, given the rapid growth in the number of emoticons and memes. However, this study is vital as it established the framework to measure sentimental influence of posts. Servi et al. (2014) introduced a novel method by devising a quantitative technique for text processing and coupled it with a statistical algorithm to find emotion patterns, a significant departure from just using links or tweets. This paper redefines online influence by emphasizing its ability to shift emotional levels expressed by social media users. It introduces a novel methodology that links changes in emotional expression patterns to specific users, using text analysis and mathematical algorithms to detect shifts and predict future trends. The study by Stieglitz and Dang-Xuan (2013) examines the impact of emotions in social media content on information diffusion, with a focus on political communication on Twitter (X). The findings reveal that emotionally charged messages are more likely to be retweeted quickly and frequently than neutral ones, highlighting the importance of sentiment analysis in understanding SI.

Social Conformation as an Influence Factor

Conformity, which involves adjusting one's behavior to align with the responses or expectations of others, plays a key role in influencing your fellow members on social media. According to Deutsch and Gerard (1955), conformity is driven by two distinct motivations: informational and normative. Informational influence arises from the need to develop an accurate understanding of reality; individuals look to others as sources of information, especially in uncertain situations, using their behavior as cues to form their own beliefs or actions. On the other hand, normative influence is driven by the desire for social acceptance and approval; individuals conform to fit into their social group or avoid disapproval. In the context of SI in OSN, these forms of conformity are critical for understanding how content, trends, and behaviors spread.

Book and Tanford (2020) offer a measurement tool by representing these complex phenomena in online networks. They confirmed that conformity significantly influenced participants' choices based on traveler reviews. For instance, when only a minority favored a green resort, subjects were less likely to choose it, conforming to the majority opinion. Those with pro-environmental attitudes felt dissonance when choosing a nongreen option, however

⁸ Dr. Herbert Simon - Nobel Laureate

evaluated their choice more favorably and sought supportive information to reduce dissonance. A study on Groupon.com indicates that social media herding can greatly enhance product awareness by spreading information and amplifying quality signals. The findings reveal that the spread of information is especially effective, with herding having a greater impact on experience, while social media influences both experience and search goods similarly (Li & Wu, 2018). Muchnik et al. (2013) illustrate that SI significantly affects rating dynamics in systems that harness collective intelligence. They discovered that it was topic-dependent, and the positive herding behavior was influenced by whether the opinions were of friends or adversaries. Similarly, Lorenz et al. (2011) show that the 'social influence effect' reduced crowd variety while increasing crowd accuracy overall and that the 'confidence impact' increased people's conviction despite the lack of enhanced accuracy. Cialdini and Goldstein (2004) examine the conformity theory as the foundation of a target's receptivity to external influences to reward human cognition. SI is shaped by group norms, primarily when individuals strongly identify with a group. Goldstein and Cialdini (2007) distinction between descriptive (what people do) and injunctive (what people should do) norms further shows that SI works through different motivational channels, impacting behaviors by reinforcing group conformity and societal expectations. Together, these theories highlight the complexity of how SI shapes individual actions. Li et al. (2011) created a model called CASINO, to study the connection between conformity and influence and how they interact based on topics in OSN. They later created a revolutionary conformity-aware cascade model CINEMA that employed a greedy algorithm to further enhance the concepts to the interconnected activities. While they employed graphical theories to understand the diffusion of influence through the networks, their approach confirmed the human behavior to conform at second and third levels (Li et al., 2015). Information shared in OSN not only shapes beliefs but also exert social pressure to conform to collective norms, thereby amplifying SI in OSN and guiding both individual and group behaviors.

Personal Brand as an Influence Factor

Scholars are keen to learn more about how personal branding affects an influencer's ability to persuade their followers in OSN. For instance, Faliagka et al. (2018) assess a social media user's personal brand strength based on their social media engagement relevancy and high level of social web activity towards an influence indication score. Their motivation is to embed this within an organization's recruiting system to choose the right candidate for the right job. Yamaguchi et al. (2020) present TURank (Twitter User Rank), a link-based system for evaluating users' authority ratings on Twitter (X) using ObjectRank highlighting that users who frequently share valuable information are considered highly authoritative. Zacharopoulos and Rigou (2021) introduces a tool for evaluating candidates' SI on Facebook, aiding recruiters in ranking applicants based on their social activity and personal branding. By allowing customizable ranking criteria and visual comparisons, the tool supports more informed recruitment decisions, linking SI on candidate suitability. Siedman (2013) research results indicate that conscientious individuals are cautious about their online self-presentation, while those high in neuroticism, agreeableness, and extraversion are more likely to express their actual selves.

The personal brand and the charisma of the influencer to continuously present themselves in the right light play a critical role in determining their influencing ability. Celebrity endorsers are used by marketers in anticipation that their fame will propagate the image of the brand or product (Erdogan, 1999). Given the prevalence of celebrity endorsement and the popularity of personal brand management, we propose to review self-presentation theory to further understand the behavior in the context of SI in OSN. Self-presentation theory, developed by Erving Goffman (1949), examines how people wish to be viewed and how they are regarded by their peers. Personal branding and self-presentation theory go hand in hand. While celebrity endorsement has long been prevalent in influencer marketing, present methodologies focus primarily on the influencer syndrome that enable everyone to become an influencer, limiting generic expertise and standard branding techniques. It is worth examining this human behavior around personal branding based on the psychological theory foundation for translation, interpretation, and measurement of SI on OSN.

Likability as an Influence Factor

We are more likely to trust others when we like them, which makes for more substantial personal and professional relationships. Networking success depends on being likable and tied to your most ingrained, enduring habits and attributes. People's willingness to comply with requests was allegedly influenced by the SI principles of likability

and interpersonal validation, especially in online environments (Guadagno et al., 2013). Taillon et al. (2020), further accentuate this idea in their research, concluding that beauty predicts favorable sentiments toward the influencer word-of-mouth, whereas similarity predicts follower word-of-mouth. Furthermore, the effect of likability on attitude toward the influencer was mitigated by proximity. Mei et al. (2015) takes a unique approach using Twitter (X) data to identify the significant hidden social attributes that create SI using the principal component analysis, rank correlation analysis, and stepwise multiple linear regression algorithms. According to their research, the three social factors that impact user influence most are popularity, engagement, and authority. The study by Li and Yin (2018) emphasizes that attractiveness and closeness as traits that positively impact social media participatory behaviors, while expertise has no significant effect. Further findings show that attractiveness is more effective in stimulating low-level participation, whereas closeness is more influential in encouraging higher levels of participation, such as content creation and contribution. Robert Cialdini has spent years studying what makes people more influential and persuasive and in his best-selling book 'Influence' asserts that likability drives persuasion (Cialdini, 2001). Qasem et al. (2017) quantifies an actor's SI as the power with which an actor may entice other significant actors into a networked community. Although the model provides the framework, it does not offer a thorough perspective into the more general element of examining all human social activities, which deserves additional research. Chekima et al. (2020) explore the shift from celebrity endorsements to social media influencers focusing on how influencer credibility—particularly attractiveness—impacts advertising effectiveness. Spokespeople with high physical attractiveness are seen as delivering more credible messages, being more expert sources, and having greater persuasive power. Although physical attractiveness enhances perceptions of credibility, expertise, and persuasiveness, social cues—such as tone of voice, facial expressions, body language, and contextual signals—exert an even stronger influence. These cues often override the effects of physical attractiveness, enhancing the perceived credibility and expertise of less attractive individuals. This suggests that leveraging social cues can be an effective strategy in communication, particularly in crisis contexts, to boost persuasiveness and message credibility (Hong et al., 2019). Myers (2021) examine how the source attractiveness model applies to top Instagram influencers, analyzing data on familiarity and likeability. More familiar influencers tend to have more followers but lower engagement, while more likeable influencers have fewer followers but higher engagement, suggesting that familiarity and likeability lead to varying social media outcomes. The study by Batenburg and Bartels (2017) found that integrating personal and professional contacts on Facebook leads to higher likability, while posting self-enhancing messages generates more respect than self-verifying messages.

Attractiveness creates an emotional connection between its supplies and its recipient. In other words, when someone wants to identify with the source, they are more likely to be persuaded by it and more inclined to identify with likable persons (Kelman, 1961). The first crucial aspect of attractiveness, according to McGuire's idea of "likability," is an attachment for the source due to physical appearance, personality, or other personal traits. (McGuire, 1985). Considering attractiveness, often equated with likability, is crucial for understanding influence as evidenced with the abundance of literature reference in that domain. Likability significantly impacts how messages are perceived and spread. Attractiveness enhances the perceived credibility, reliability, and appeal of a person or message, making users more likely to engage, share, and adopt the behaviors or opinions being communicated. In OSNs, where content competes for attention, spokespeople with high attractiveness can more effectively capture interest, drive engagement, and shape trends or opinions, thereby amplifying their SI. So, it is prudent to consider that within the measure of SI.

Dynamic Social Impact as an Influence Factor

Many aspects of our lives have been affected by the ability of an individual to cause social impact, creating shifts in our thoughts and behaviors. Social impacts are weighing increasingly heavily on people's decisions, from how we assess how organizations operate to the products we buy. Traditionally, the focus has been on how leaders influence their followers. However, Oc and Bashshur (2013) highlight that followers also have a dynamic impact on leadership, particularly in shaping leader behaviors reviewing through the lens of social impact. Miller and Brunner (2008) looked at the Social Impact Theory to better understand the origins and goals of interpersonal impact during network-generated interactions. They discovered that exaggeration and assertiveness were the two behavior qualities significantly contributing to influence compared to emotional intensity and sensitivity. DiFonzo et al. (2011) indicate that group-level characteristics like cohesiveness and follower count matter along with individual factors of an influencer, such as strength and availability. They explore rumor as a form of SI, focusing on three key aspects:

shared sensemaking, rumor propaganda, and rumor spread. They identify that rumors can shape expectations and have been strategically used in misinformation and propaganda campaigns, with malicious intent sometimes driving their origin or spread. The study by Bullock (2007) examined how facial attractiveness, weight, and immediacy affect SI in dyadic online discussions, and results showed that attitudes became more similar and interrelated over time in line with the impact.

Latane's (1981) Social Impact Theory is based on the idea that society is a complex, self-organizing system comprising inter-dependent individuals who each abide by basic social impact principles, and a person's susceptibility to SI depends on the group's strength, proximity and size of the group. The Dynamic Social Impact Theory aims to explain how social impact affects behavioral changes, subjective sensations, and emotions. The theory seeks to explain the changes in the OSN group resulting from the SI exerted by the influencer and is captured by the individual impact they exert through their actions and interactions (Latane, 1996). So, it is most certainly worthy for scholars and researchers to understand and experiment with the interrelation between the individual ability to dynamically impact the social behaviors that would connect to their ability to influence fellow social media users.

Expertise as an Influence Factor

Expertise is widely regarded as the most critical social attribute in creating influence. Psychological studies over the decades have confirmed that people gain trust when they understand and agree with each other's intentions from expertise (Ericsson & Smith, 1991). While experts' capability to influence their followers on social media is highly valued, few scholars understand how user-generated content links to a social media user's expertise, much alone how this relates to the content creator's influencing power. The Expertise Theory, as defined by Goodall (2012), emphasizes that expertise emerges through a combination of inherent knowledge, practical skill (or craft), and the full acquisition of technical and business acumen. Goodall's theory highlights that expertise is not only about formal training but also involves immersive observation, empathy, and a deep understanding of the domain, achieved through sustained engagement and experience. When translating, interpreting, and measuring SI in OSN, the increasing importance of expertise in shaping and guiding the growing volume of content must be emphasized. Extensive academic research, experiments, and surveys have been conducted to explore how experts affect societal dynamics and, more importantly, how their expertise enhances an influencer's ability to persuade and engage their followers on OSNs.

Zhao et al. (2016) developed a computational method for determining the relationship between expertise and influence and found that high-knowledge users had the ability to exert influence even outside of their area of expertise. Influencer expertise is more significant than the topic's relevance, as top experts often encourage their audiences to engage with topics outside their expertise. These insights provide a deeper understanding of influence variation and the role of expertise in social media. Hall and Blanton (2009) investigate the role of normative expertise as a moderator of SI and its effects on behavioral intentions and actions. The findings suggest that when speakers with normative expertise praise an action to encourage it, they may unintentionally imply that the action is uncommon, potentially weakening their influence on behaviors shaped by normative perceptions. In contrast, speakers without normative expertise can frame messages differently without altering normative assumptions, allowing them to influence behavior more effectively. Askarisichani et al. (2020) find that individuals with greater expertise and social confidence tend to exert more influence, whereas low-performing group members often underestimate the expertise of their higher-performing teammates. The study's hypotheses, supported by empirical evidence, draw on theories such as transactive memory systems, social comparison, and confidence heuristics.

van der Valk (2017) investigated how social media interactions influence decision-making without face-to-face communication. The findings revealed that participants exposed to an expert's opinion improved their judgment accuracy, while those influenced by a novice saw a decrease in accuracy. Additionally, decision confidence increased across all groups, and trust levels were significantly higher for experts than for novice or neutral peers. Identifying topic-based influencers is a common technique in social media, largely because these influencers are often considered experts in their respective areas. Alp and Oguducu's (2018) research seek to identify topical experts on Twitter (X) by combining network structure with user activities related to specific topics. The approach leverages user-specific features, such as topical focus rate, activeness, authenticity, and response speed, to pinpoint influencers who demonstrate expertise in particular areas. Similarly, Fang et al. (2014) proposes a Topic-Sensitive Influencer Mining

(TSIM) framework to identify topic-level experts in interest-based social media networks. Unlike traditional approaches focusing solely on textual information or general influence, they use hypergraph learning to capture various relationships, including visual-textual content and social links between users and images, to identify experts who are topic-specific influencers. Kong and Feng (2011) propose a method to identify and rank influential authors on micro-blogs, focusing on users who post high-quality, topic-specific content. The quality of a tweet is determined based on its topic focus, retweet behavior, and the topic-specific influence of users who retweet it, extending user relationships beyond the traditional follower-friend model to more dynamic, tweet-based interactions. Weng et al. (2010) tackle the challenge of identifying influential users on micro-blogging platforms like Twitter (X), where users can follow others freely. To measure influence, they propose "TwitterRank," an extension of the PageRank algorithm that incorporates both topical similarity and network structure to identify true influencers based on their expertise in specific topics. However, with the evolution of Twitter (X) and changes in its algorithmic structure, the relevance of TwitterRank is not relevant, however the idea of relying on expertise to identify the influencer retains relevance. Liu et al. (2012) offer a generative graphical model that extracts topic-level impact strength from a diverse array of links and rich content associated with each user in the network to determine influence propagation, both conservative and non-conservative, to derive aggregation mechanisms. Hamzehei et al. (2017) consider user-generated material and user interactions within network topology to assess topic-based influence and their experiments with a Twitter (X) dataset demonstrate that their approach effectively measures user influence based on topic expertise. Tang et al. (2009) present topical affinity propagation to model topic-level social impact on vast networks to answer the fundamental challenges of measuring and differentiating SI. Their approach analyzes topic-based SI and enhance expert finding in social networks. Using a graphical probabilistic model and a scalable algorithm the approach effectively identifies topic-specific influences. Zhaoyun et al. (2013) aim to identify true influencers in micro-blogging contexts like Twitter (X), where large numbers of users can discuss any topic but vary greatly in influence. To measure user influence based on expertise, the study analyzes multi-relational interactions such as retweets, replies, reintroductions, and reads through random walks using a novel method to handle the uncertainty in reintroduce and read operations and to determine transition probabilities in uncertain networks. The proposed approach also accounts for both intra- and inter-network transitions in a combined random walk model to effectively identifying influencers.

Opinion Leader as an Influence Factor

People often become opinion leaders in a culture when they provide helpful interpretations of daily life and current events that help others, mainly when important events occur. So, locating them helps us identify the influencers. Popular YouTubers and Instagrammers frequently serve as today's thought leaders. Because of this, there is more interest in understanding, quantifying, and predicting how these opinion leaders' influence will grow in OSN (Rogers & Cartano, 1962). The Two-Step Flow of Communication hypothesis by Katz and Lazarsfeld (1959) explains that media messages influence the public indirectly through opinion leaders, who first absorb and interpret the information. These leaders, viewed as credible and knowledgeable, then share and contextualize it with their social circles, shaping opinions and behaviors. This model highlights the critical role of interpersonal communication in public influence and serves as the foundation for understanding how opinion leadership originates and operates. In that regard, Bergsma et al. (2014), used machine learning to develop a methodology based on scientific and non-scientific aspects that precisely quantifies the researcher's influence while considering their interpersonal, cognitive, behavioral, and linguistic abilities. A different approach was taken by Oro et al. (2017), who concentrated on utilizing social media to more accurately gauge the acceptance of themes and viewpoints to identify opinion leaders. The volume of citations, number of contacts, comments from followers, and the overall network activity monitoring are ways to gauge the influence of opinion leaders. Afridiana et al. (2019) investigate the influence of opinion leader postings on Instagram to determine how educational content shared by popular figures affects millennials' intention to pay zakat. Utilizing the Theory of Planned Behavior and Source of Credibility, the study evaluates four opinion leaders based on their expertise, trustworthiness, and attractiveness. Zhao et al. (2018) investigate opinion formation in e-commerce communities, focusing on how opinion leaders influence group opinions. They develop a bounded confidence model to simulate opinion evolution by categorizing social agents as either leaders or followers. The study finds that opinion leader influence is shaped by their proportion, followers' confidence levels, and trust. Ma and Liu (2014) introduce the SuperedgeRank algorithm, an innovative approach for identifying opinion leaders by integrating social network analysis, text mining, and super network theory. They establish a super network model with multidimensional subnetworks to evaluate and identify key influencers within the network. Bodendorf and

Kaiser (2009) present a novel approach that uses text mining and social network analysis to identify opinion leaders and trends, offering a deeper understanding of how opinions are formed in OSNs. van Eck et al. (2011) explore the crucial role of opinion leaders in adopting new products, finding that these leaders not only hold central positions in networks but also possess more accurate product knowledge, show more significant innovation, and are less swayed by social norms. Farivar et al. (2021) explores the combined influence of opinion leadership and parasocial relationships on followers' purchase intentions in influencer marketing, revealing that parasocial relationships have a more significant impact than opinion leadership, particularly when storytelling posts are employed.

Credibility as an Influence Factor

Credibility may be traced back to Aristotle's Rhetoric theory. According to Aristotle, rhetoric is the capacity to recognize what may be convincing in any situation. It simplifies your life if you have credibility and people know, like, and trust you, as you are not required to prove yourself (Zeller, 1897). According to the Source Credibility Theory, individuals are more likely to be convinced when the source appears credible (Hovland & Weiss, 1951). Academics should have a genuine interest in understanding the impact of credibility on an influencer's capacity to persuade their followers and the effect of other social and innate psychological behavior traits to get to an accurate measure of SI.

Increased communication on diverse topics builds credibility (Huffaker, 2010). The findings indicate that online leaders influence others through active communication, high credibility, central roles within their networks, and the use of affective, assertive, and linguistically diverse messaging. Abu-Salih (2020) underscores the importance of comprehensively understanding the contextual credibility content of social media users to measure their SI accurately. The study proposes a time-aware framework for estimating and predicting credibility in OSN based on user activity in specific domains. The approach incorporates semantic and sentiment analyses to assess the content produced by users and introduces a set of advanced attributes to measure accurately influential users within designated domains, demonstrating its practical applicability. Alrubaian et al. (2017) propose a novel approach combining a user's reputation on specific topics and their sentiment to identify credible sources. A new reputation metric is introduced, incorporating unique features beyond existing models. By incorporating sentiment analysis, it evaluates both a user's reputation on a specific topic and their sentiment in discussions, leading to a significant improvement in the accuracy of identifying topically relevant and credible sources of information on Twitter (X). The study's introduction of a new reputation metric that includes sentiment features demonstrates the approach's effectiveness, outperforming traditional machine learning methods. Khrabrov and Cybenko (2010) created a metric system for identifying people with rising influence based just on the format and tempo of their conversations. They saw context with its own "mind economy," which could be manipulated to improve participant rankings. Scheinbaum and Wang (2018) were among the few who sought to build their algorithm based on this theory and confirmed that trustworthiness was the one quality that consumers found to be most compelling.

The conclusion only reinforced advertisers to utilize reputable celebrity endorsers with a worldwide appeal to boost brand reputation. In a similar vein, Wiedmann and Von Mettenheim's (2021) study examined, via the lens of the source-credibility model, how success criteria were more closely related to influencers than to the data in their profile to illustrate the necessity for credibility and trustworthiness. Wijesekara and Ganegoda, (2020) develop a machine learning model based on user reputation to estimate the source credibility of the Twitter (X) feeds. This provides a better understanding of the credibility impacts influence on social media. Hu et al. (2019) study reveals that peers' expertise and trustworthiness are key elements of source credibility, significantly affecting both informational and emotional SI on consumers. These credible sources facilitate influence, particularly in the social commerce setting, contributing to impulsive purchasing behaviors. The findings emphasize the importance of source credibility in shaping consumer decisions in social commerce, which integrates social media and commerce, enabling users to discover, share, and purchase products directly through social platforms.

DISCUSSION

This discussion synthesizes findings uncovering key themes that deepen our understanding of how SI functions within the ever-changing digital landscape. While theoretical research has successfully conceptualized the role of human behavior in SI, its insights often remain fragmented, reflecting the complexity of influence across diverse

platforms and contexts. The vast content generation capabilities of OSNs further intensify these dynamics. Moreover, the rapidly evolving nature of online influence and the continuous surge in digital content demand innovative approaches to building, measuring, and sustaining influence. By examining these interconnected elements, this discussion provides valuable insights and practical implications for researchers, practitioners, and marketers seeking to refine their understanding and application of SI in OSNs.

Fragmented landscape

The literature review, centered on human behaviors to understand SI in OSNs, showcases a pattern of the tendency of the scholars to a narrow focus on select, easily measurable human characteristics, resulting in an incomplete grasp of the concept's complexity. SI is often oversimplified when studies isolate its definition to single traits or frameworks that lend themselves to quantification, making it challenging to develop a comprehensive measure. For instance, some scholars emphasize the influencer's likability (Guadagno et al., 2013), personal branding (Faliagka et al., 2018), or dynamic social impact (Oc & Bashshur, 2013) as core indicators of SI. Other studies consider social conformity (Muchnik et al., 2013), shared sentiments (Bae & Lee, 2012), or social contagion (Christakis & Fowler, 2013) as the driving factor. Common interests (Ji et al., 2015), relationships (McPherson et al., 2001) and social capital (Badawi et al., 2019) are well studied to be creating a significant impact on determining SI in OSN. Additionally, character traits like expertise (Zhao et al., 2014), credibility (Alrubaian et al., 2017), and opinion leadership (Bergsma et al., 2014) contribute further unique dimensions to understanding and applying SI in digital contexts. While these perspectives bring valuable insights, they represent only isolated fragments of a much broader influence landscape. This wide range of definitions and approaches highlights the challenge of creating a unified, robust measure of influence. The difficulty lies not only in pinpointing what constitutes influence but also in capturing its complex, multifaceted nature across various social contexts and behaviors within OSNs. This lack of cohesion and fragmented approach to measuring human behaviors significantly constrains current research, hindering the development of reliable and universally applicable metrics for SI in OSN.

Proliferation of Massive Content Across Multiple OSNs

Humans are inherently social beings, and their widespread adoption of social media has revolutionized how they communicate and interact. The rapid expansion of social media, now encompassing approximately 5.17B users globally—more than doubling from 2.07B in 2015 (Dean, 2024)—has significantly increased both the volume and diversity of the social media landscape. With millions of new users joining platforms like TikTok, LinkedIn, and Instagram, and an average user engaging with about 6.7 platforms simultaneously (Dean, 2024), the dynamics of SI have become increasingly complex. The sheer volume of daily content generation is staggering - users produce 2.5 quintillion bytes of data daily (Marr, 2018), and IBM reports that 90% of the data in use today was created in just the past two years. This explosion in content volume poses immense challenges for tracking and measuring SI. Traditional metrics such as follower counts, and engagement rates fail to capture the nuances of platform-specific behaviors. For example, Instagram's visually driven environment fosters different interaction patterns compared to TikTok's focus on viral video trends or Reddit's real-time discussions within niche communities. Each platform introduces unique communication styles and engagement dynamics, requiring SI to be contextualized. Moreover, users' fragmented behaviors across platforms add to the complexity—an individual influential on Instagram might engage differently on TikTok or Twitter (X). The rise of niche communities, emphasizing deeper interactions and specific interests, further diversifies how SI is exerted, often transcending conventional metrics in favor of meaningful engagement. As a result, measuring SI necessitates a dynamic and multifaceted approach that considers the increasing content volume, platform diversity, and the ever-evolving patterns of influence.

Everyone is an Influencer

In the age of social media, the power to influence is no longer reserved for celebrities or public figures—everyone has the potential to be an influencer. Influencer endorsements on platforms like Instagram significantly shape consumer behavior, whether it comes from a local neighbor or global celebrity like Kylie Jenner⁹, driving massive sales spikes (Mulcahy et al., 2024). The 'State of Influencer Marketing' (Influencer Marketing Hub, 2024) accounts for this with

⁹ Kylie Jenner – American media personality and socialite

the fact that the industry has grown into a \$21.1B powerhouse. With platforms such as Instagram, TikTok, Twitter (X), and LinkedIn enabling diverse content creation, even users with small followings can make a substantial impact through authentic, relatable content. The recognition of nano, micro, and macro-influencers further exemplifies this trend, as macro-influencers achieve 5% to 25% engagement and micro-influencers reach 25% to 50%, proving that influence spans far beyond just a handful of high-profile figures (Conde & Casais, 2023). The democratization of influence allows personal experiences, niche interests, and unique perspectives to spread widely, often resonating more deeply than polished, professionally curated messages. As users share, comment, and react to content within their networks, they amplify their voices and play a pivotal role in shaping conversations and social norms. This transformation of influence demands a more dedicated and strategic approach to understanding and leveraging the power held by a wide range of social media users.

Quantifying Human Emotions

Social relationships are built on trust and shared goals within groups or networks, making their understanding critical to studying influence. Academics have long explored how these relationships are represented (Anagnostopoulos et al., 2008) and measured (Cataldi et al., 2013) in online social networks (OSNs). Meeker's (1971) foundational model suggests that interpersonal exchanges function as individual decision-making processes. However, a significant challenge lies in assessing the broader emotional connection between influencers and their audiences, as highlighted by Ferrara and Yang (2015). The lack of in-person interaction and vocal inflection makes detecting subtleties such as irony even more difficult in traditional OSNs. This challenge intensifies in the metaverse¹⁰, where communication shifts to immersive environments. Sentiment measurement becomes even more critical as trust and emotional bonds are conveyed through avatars, virtual gestures, and digital settings. These multimodal forms of expression require advanced tools to interpret nuanced emotional signals, ensuring that authenticity and trust are preserved in this evolving virtual landscape. Sentiment research must go beyond words because social media users rapidly adopt memes, emojis, and emoticons. Memes were created by human culture, spread through language, and then competed for viewers' attention on the internet, one of the world's most significant testing grounds. Since they are flexible and can respond to changing conditions incredibly quickly, memes can serve as containers for various viewpoints because humor weakens audiences' natural defenses (Tiffany et al., 2018). Similarly, using emojis in social media and digital messaging with or in place of words to convey an idea, entity, sentiment, status, or event has gained immense popularity. We could even refer to them as contemporary hieroglyphics (Blagdon, 2013). They are currently regarded as significant in both Western and global popular culture. The Face with 'Tears of Joy' emoji was selected as the word of the year for 2015 by Oxford University Press (2024). Any measure of SI in OSN must be flexible to adapt to this new communication form.

Fake Accounts, Bots and Deepfakes

Several studies (Lorenz et al., 2011), (Huffaker, 2010) have relied on an influencer's 'number of followers' or 'number of friends' as a straightforward numerical interpretation. This archaic 'follow for follow' pattern has led to network growth without authentic relationship-building or genuine interest misleading the true influential quotient. This pattern is getting even worse with the advancement of technology, which allows anyone to purchase followers and add automated bots or bogus profiles made by robots. A new phenomenon called click farm¹¹ has started to plague social media platforms. These farms offer 'followers' to be purchased in bulk for a cost (Paquet-Clouston et al., 2017). Automated bot followers that mimic real users, are making it increasingly difficult to distinguish between genuine accounts and fake profiles as these bots blend seamlessly with real user activity (Haustein et al., 2016). Although several cutting-edge tools are continuously working to eliminate fraud and phony accounts, there are no international laws or audit regulations that would deter the behavior. Tracing the distribution of information within the network and determining its origin presents a problem across all social network applications (Anand et al., 2020). Deepfakes are another form of synthetic media that uses artificial intelligence techniques and intense learning algorithms to create highly realistic but entirely fabricated videos, audio recordings, or images (Mirskey & Lee, 2021). These manipulations can convincingly depict individuals, leading to concerns related to misinformation, privacy, and potential harm. Deepfakes have raised critical ethical, legal, and technological challenges, necessitating ongoing

¹⁰ Metaverse is iteration of the Internet as a single, universal and immersive virtual world

¹¹ A click farm is a form of click fraud

research and countermeasures to detect and mitigate their impact on society (Chesney & Citron, 2019). The inherent prevalence of fake accounts, bots, and deepfakes in OSNs poses a persistent challenge to create a mechanism that would accurately measuring SI in OSN.

LIMITATIONS OF THE STUDY

While this study provides valuable insights in comprehending SI in OSN, the limitations must be acknowledged. These include potential biases in the thematic categorization and context of human behaviors, as well as methodological constraints related to the selection and synthesis of diverse literature. The rapidly changing nature of social media and the inherent complexity of defining and measuring SI add further constraints. These limitations underscore opportunities for future research to build on the current work, addressing these constraints and enhancing the understanding of SI in digital spaces.

Potential Bias in Thematic Categorization and Context

The interdisciplinary nature of SI research required synthesizing studies from diverse fields, each with unique terminology and context, creating challenges in achieving a coherent integration of findings, especially when the behaviors were mapped to the associated psychology theory. The subjective grouping of behaviors into categories posed the risk of bias, as different researchers might categorize the literature differently. Moreover, the context-specific focus—whether based on platform, demographics, or geography—may have limited the generalizability of the findings and potentially overlooked more subtle forms of influence, such as passive consumption. To mitigate these biases, the review process was structured across multiple stage, with all four authors from diverse background and geography, critically challenging and refining the categorizations, thereby enhancing the rigor and reducing the potential for subjective bias.

Time-Bound Constraints and Rapid Evolution of the Field

The fast-evolving nature of social media trends and technologies, including platform developments and the rapid growth of AI and Gen AI technologies, poses challenges to the relevance of identified behaviors over time. Many of the reviewed studies are cross-sectional, offering only a snapshot of current behaviors without accounting for their long-term evolution as platforms and user interactions change. While the literature coverage is extensive, it may not fully capture emerging trends, highlighting the need for continuous updates as the field progresses rapidly. However, the value lies in linking these behaviors to proven psychological theories, providing a timeless component to the evaluation and ensuring that core principles of SI remain applicable despite technological advancements.

Subjective Nature of Measuring SI

Measuring SI based on human behaviors is inherently complex due to factors like cultural differences, ethical considerations, and the interconnectedness of behaviors, all of which make researching the topic inherently difficult. The definition of influence varies widely across contexts, platforms, and user perceptions, complicating efforts to isolate individual behaviors. Maybe it was this complexity that resulted in the search results dominantly to be either conference papers or studies that have used graphical or scientific methods to capture behavior patterns. We believe that itself offers a unique value to this research paper laying the ground in providing a unique behavioral perspective for further interesting research.

IMPLICATIONS

This focused review not only catalogs the present-day research, but also lays a solid foundation for future that paves the way for establishing universally accepted standards for SI measurement in OSN. We recommend that researchers develop a flexible model that allows both horizontal adaptability—enabling the inclusion or exclusion of different theoretical dimensions—and vertical depth, providing the ability to delve deeper into specific behavioral aspects, such as sentiment analysis. The potential for further exploration and application of our findings promises significant advancements in academic, knowledge and industry practices.

Academic Implications

Our focused literature review, meticulously cataloging studies up to 2021 that measure SI in OSN, stands out for its emphasis on human behavior characteristics. While most studies in this area focus on graphical theories and structural network topological attributes, our review offers a meaningful examination of psychological and sociological behavior theories. It enriches the theoretical understanding of SI by offering a multidimensional perspective that connects theories to specific behaviors in digital contexts, providing a clearer conceptual insight. This structure serves as a foundation for future research to explore the nuances of human behaviors across various contexts and fosters cross-disciplinary integration, addressing the often-fragmented nature of SI studies across fields like psychology, graph theory and social networks. Clarifying complex constructs, the categorization breaks down SI into more digestible components, enhancing the ability to isolate and study specific aspects of influence. The consolidated understanding encourages methodological innovations, prompting sophisticated data collection and mixed-method approaches. Overall, this categorization not only advances theoretical clarity but also bridges the gap between academic inquiry and real-world application, enhancing the study of influence within the rapidly evolving landscape of OSNs. Our research has established a foundation for a sustainable theoretical framework that predicts a quantifiable measure of SI by integrating perspectives on twelve pivotal human behaviors. By focusing on the actions and outcomes of human behaviors in social media, particularly how they may evolve behind a keyboard or a click, we provide a transparent analysis of twelve identified human behavior traits across various characteristics. Our summary of the limitations of current approaches and the merits of potential avenues for further research fosters intrinsic curiosity, encouraging researchers to build upon this study with practical ideas and innovative strategies for implementation. The potential for further research and development is significant, inspiring and engaging the audience.

Industry Implications

Understanding SI in OSN has significant industrial implications across various domains. Influencer marketing has revolutionized consumer engagement, with platforms like Instagram and TikTok enabling several consumer brands leverage influencers to increase product visibility. Campaigns such as TikTok's viral #GucciModelChallenge¹² or Instagram's Chiara Ferragni's¹³ posts, exemplifies the power of SI by driving consumer engagement and brand loyalty through partnerships with global brands. Political landscapes have been equally affected, as demonstrated in recent elections and social movements worldwide, where SI plays a crucial role in shaping voter opinions, mobilizing support, and spreading messages rapidly, as seen in the U.S. presidential elections 2016, 2020 and 2024, and the European Parliament campaigns including Brexit¹⁴. The COVID-19 pandemic further highlighted the power of SI, as social media became a primary channel for disseminating information on public health guidelines, vaccination drives, and community support, but also misinformation. Social culture has evolved as well, with movements like #BlackLivesMatter¹⁵ and #MeToo¹⁶ gaining momentum through SI on social media platforms, amplifying social justice causes globally. E-commerce platforms like Amazon¹⁷ and Etsy¹⁸ use SI principles by encouraging user reviews and ratings, which heavily influence purchasing decisions. Similarly, Starbucks¹⁹ utilized SI by promoting user-generated content through campaigns like #RedCupContest²⁰ to drive engagement and brand loyalty. Streaming services like Netflix²¹ and HBO²² have capitalized on SI by encouraging social discussions around shows such as Stranger Things or Game of Thrones,²³ turning them into cultural phenomena and enhancing viewership through

¹² #GucciModelChallenge involves distilling a 'Gucci look' into staples that are probably already in everyone closet.

¹³ Chiara Ferragni - An Italian blogger, businesswoman and a fashion influencer on Instagram with 29 million followers.

¹⁴ Brexit - An abbreviation of 'Britain' and 'exit' referring to the withdrawal process of the UK from the EU.

¹⁵ #BlackLivesMatter – A decentralized social movement that highlights the discrimination experienced by black people and promote anti-racism.

¹⁶ #MeToo - An international campaign to denounce sexual assault, rape, and harassment.

¹⁷ Amazon – Multinational technology company and the largest retail marketplace globally.

¹⁸ Etsy - An American ecommerce website focused on selling handmade and vintage items.

¹⁹ Starbucks – An American multichain coffee house and roastery reserves headquartered in Seattle.

²⁰ #RedCupContest – Instagram contest encouraging consumers to show their creativity in using Starbucks Red Cup.

²¹ Netflix - An American subscription video on-demand over-the-top streaming service

²² HBO – An American pay television network, a unit of Warner Bros.

²³ Stranger Things and Game of Thrones – Popular series on HBO

word-of-mouth buzz. These examples highlight SI's ability to shape consumer behavior, mobilize communities, and influence public sentiment, making it a critical tool for businesses and public organizations to refine strategies in today's digital age. Companies and public sectors can leverage these insights to enhance communication strategies, drive behavioral change, and better understand consumer sentiment, making SI in OSNs a critical aspect of influencing and navigating today's digital society.

DIRECTIONS FOR FUTURE STUDY

Merits of Exploring the Synergies between the Twelve Human SI Factors

The Yellow Jacket²⁴ movement in France exemplifies how human behaviors drive SI through collective action. What started as a protest against fuel taxes by a few individuals, soon grew into a movement that united people through Facebook, bound by a shared sense of injustice and common interests. Over time, the protesters built strong relationships through consistent exchanges within the group, facilitated by the OSNs, allowing for sustained influence and collective action (Gauthier, 2022). The movement demonstrated how common interests and relationship building can lead to the accumulation of social capital, which helped the Yellow Jackets maintain influence to create a meaningful revolution.

The AMC short squeeze²⁵, orchestrated by retail traders on Reddit's WallStreetBets²⁶, highlights SI fueled by shared sentiments, emotional contagion, and social conformity. The rapid spread of the idea to collectively buy AMC shares ignited a wave of emotional group responses, with participants driven by fear of missing out or a collective rebellion against institutional investors (Mancini et al., 2022). This emotional contagion led to massive price fluctuations, demonstrating the power of immediate, group-driven influence. Social conformity played a pivotal role, as many retail investors followed the crowd despite significant financial risks.

Elon Musk²⁷, renowned for his influential tweets, exemplifies how individual likability and personal brand promotion through self-presentation create dynamic impact. For instance, his tweet about Dogecoin²⁸ caused immediate market fluctuations (Ante, 2023). Musk's tech-savvy image and vast follower base amplify his dynamic social impact, as people react swiftly to his opinions by trading based on his statements, demonstrating how an individual can wield significant dynamic social impact in real time through likability and personal brand.

Greta Thunberg²⁹ represents sustained, long-term SI through her credibility, expertise, and opinion leadership. Her persistent climate advocacy on social media and beyond has established her as a trusted opinion leader in the environmental movement (Sabherwal et al., 2021). By consistently sharing knowledgeable and ethically grounded messages, Thunberg has influenced global public opinion and policy discussions, illustrating how long-term credibility can shape SI across diverse platforms.

These examples reveal the intricate interplay of human behaviors in shaping SI within the twelve identified human behavior factors. Future research should empirically validate these synergies and explore how these dynamics vary across social media platforms, demographics, and cultural settings. Such validation is essential for refining the theoretical understanding of SI and enhancing its practical applications in digital environments.

Merits of Concept Modeling Approach

Continuing to investigate and enhance behavior modeling as a representation of SI theories is crucial. With a robust foundation from existing literature, particularly concerning twelve human behaviors based on psychological theories and consolidated propositions based on lay theories, further examining these concepts is prudent. Creating a framework and modeling this concept brings structure, clarity, and efficiency to the process, making it an invaluable tool for addressing complex issues, decision-making, and process management (Humphrey et al, 2010). The approach of deconstructing abstract concepts into manageable elements validated by experts enhances

²⁴ The Yellow Vests Protests – A series of populist, grassroots weekly protests in France that began on 17 November 2018.

²⁵ AMC – short squeeze is short selling information for shares of AMC Entertainment Holdings Incorporated in 2021.

²⁶ WallStreetBets – A subaccount within Reddit groups that played an active role in AMC short squeeze.

²⁷ Elon Musk – A billionaire social entrepreneur and political influencer

²⁸ Dogecoin – A cryptocurrency created by software engineers Billy Markus and Jackson Palmer

²⁹ Greta Thunberg – a social climate activist

comprehension, supports theory development, and fosters critical thinking. Ultimately, this method contributes to a more informed and comprehensive framework and model for addressing various challenges and subjects (van Ingen et al., 2021). In a unique attempt by van Maanen and van der Vecht (2014), Cialdini's model (2011) of SI was simulated using agent-based modeling. Using a Dutch television show as a use case, they demonstrated the ability to model SI on Twitter (X) backed through five progressive versions of decision models (van Maanen & van der Vecht, 2013). However, they were very restrictive in adapting variables that characterized human behavior traits. Even with that limitation, this is very promising research as it provides transparency to measuring SI based on human behaviors. We anticipate that the social scientists will be prepared to work together on multidisciplinary modeling initiatives to further examine the intricate dynamics of problems like SI informed by the detailed literature review and proposition presented.

Merits of AI and Deep Learning

Similarly, it is vital to capitalize on deep learning advancements to understand SI across multiple OSNs to accentuate understanding human behaviors. Scholars have expressed increased interest in taking advantage of the growing art of the science of machine learning and deep learning algorithms to represent and measure human behaviors in OSN (Tang et al., 2009) (Cataldi et al., 2013). The theoretical framework based on the dual-process and social influence theory was conceptualized by Kwon et al. (2021) in which they empirically investigated a significant amount of actual customer review data. While their study had limitations, it captured restrictive data sets and qualitative feature sets that covered comprehensive factors across domains that explained the human decision-making process. This cutting-edge neural network model faced two common problems, as with any deep neural network: interpretability and scalability. Even with those inherent limitations, there is an opportunity to examine human behavior-based traits and discover an equivalent system model to express and quantify SI in OSN. Another aspect where deep learning will be very useful is in sentiment analysis of the contents. The user's SI depends on how popular and emotional they are about a specific topic. The user's engagement, outreach, sentiment, and growth attributes determine the impact of SI. Sentiment influences perception, credibility, and how individuals respond to such stimuli (van Kleef, 2009). Academics are, therefore, increasingly interested in understanding how user sentiments and emotions affect influence (Zhang et al., 2018). Researchers must weigh sentiment analysis to understand the intricacies of the SI human behaviors in response to the industry's expanding interest.

Merits of Systems Thinking

Systems Thinking is a school of thought that focuses on recognizing the interconnections between the parts of a system and synthesizing them into a unified view of the whole (Kim & Anderson, 1999). The psychology, motivations, and emotions that drive user actions must be considered to create a more cognitive measure (Cabrera et al., 2015). Systems thinking is a valuable approach to understanding SI in OSN as it involves analyzing complex systems and considering the interconnections and feedback loops among various components. The key aspects of using systems thinking to comprehend SI would aid in recognizing the eco-system's interconnected elements and non-linear dynamics. Systems thinking recognizes that social media ecosystems are interconnected, including users, content, algorithms, and platforms (Finegood et al., 2014) These elements interact dynamically, impacting each other and the overall system, and any model must consider these dynamic aspects comprehensively. It also acknowledges that cause-and-effect relationships in social media are often non-linear. Small changes can have disproportionately large effects due to the networked nature of the platforms. Social media systems can exhibit emergent behaviors, which are outcomes that result from the interactions between components but are not explicitly designed. Viral trends, echo chambers, and the spread of misinformation are examples of emergent behavior driven by SI. It highlights potential unintended consequences when attempting to influence social media systems (Stroh, 2015). Systems thinking recognizes the sensitivity of social media systems to initial conditions. A small change or introduction of an influential user can lead to significant shifts in the system's behavior. Also, changes in SI and their consequences may take time. A social media user's thoughts and knowledge may evolve, and its effects on opinions or behaviors may take a while to become apparent. Given the dynamic nature and complexity of the ecosystem, it is vital to have a feedback loop so the model can use retrospectives to learn and continually evolve. Understanding these loops is crucial to grasp the amplifying effects and identify points of intervention. By understanding the system's dynamics, policymakers, researchers, and platform operators can identify areas where they can influence or regulate SI for desired outcomes, such as mitigating the spread of disinformation or promoting positive behaviors.

CONCLUSION

The primary goal of this focused literature study was to find relevant scholarly and scientific evidence to evaluate and synthesize appropriate metrics to measure SI in OSN. Consequently, 88 papers were reviewed in-depth, answering research questions, identifying related theories, assessing the content in the light of psychological traits, and analyzing approaches for their merits and usefulness. This study makes a noteworthy academic contribution to the field of research by summarizing the state-of-the-art studies on SI in OSN. While methodological weaknesses and limitations were inherent, we also investigated merits for continued research by pointing up connections in the literature and augmenting with merits on a few approaches for consideration. Continuing this research by exploring the directions for future study and beyond will enable academics to establish a standard cognitive measure for SI in OSN. This will help extend the proliferation of capitalizing on an individual's SI and, more importantly, benefit the influencer in understanding their worth and monetizing their SI. Commercial entities can also benefit from standardized and regulated governance.

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APPENDIX – 1 (SELECTED JOURNALS FOR THE LITERATURE REVIEW)

COMMON INTEREST – SOCIAL IDENTITY THEORY	
1	Ji, L., Liu, J. G., Hou, L., Guo, Q. (2015). Identifying the role of common interests in online user trust formation. <i>PLoS ONE</i> , 10(7), 121105–121105. https://doi.org/10.1371/journal.pone.0121105
2	Bilal, M., Marjani, M., Hashem, I. A. T., Malik, N., Lali, M. I. U., & Gani, A. (2021). Profiling reviewers' social network strength and predicting the "Helpfulness" of online customer reviews. <i>Electronic Commerce Research and Applications</i> , 45, 101026. https://doi.org/10.1016/j.elerap.2020.101026
3	Bergin, D. A. (2016). Social influences on interest. <i>Educational Psychologist</i> , 51(1), 7-22. https://doi.org/10.1080/00461520.2015.1133306
4	Shi, L.-L., Liu, L., Wu, Y., Jiang, L. & Hardy, J. (2017). Event detection and user interest discovering in social media data streams. In <i>IEEE Access</i> , 5, pp. 20953-20964. https://doi.org/10.1109/ACCESS.2017.2675839
5	Zhou, X., Wu, B., & Jin, Q. (2018). Analysis of user network and correlation for community discovery based on topic-aware similarity and behavioral influence. <i>IEEE Transactions on Human-Machine Systems</i> , 48(6), 559–571. DOI: 10.1109/THMS.2017.2725341
THEORY	Tajfel, H., & Turner, J. C. (1986). The social identity theory of intergroup behavior. Worchel, S, Austin, G. W., eds., <i>Psychology of Intergroup Relation</i> , 7–24. Hall Publishers. http://christosaoannou.com/Tajfel%20and%20Turner%201986.pdf
RELATIONSHIP – SOCIAL EXCHANGE THEORY	
6	McPherson, M., Smith-Lovin, L., Cook, J. M. (2001). Birds of a feather: Homophily in social networks. <i>Annual Review of Sociology</i> , 27, 415–444. https://doi.org/10.1146/annurev.soc.27.1.415
7	De Choudhury, M., Sundaram, H., John, A., Seligmann, D. D., & Kelliher, A. (2010). " Birds of a Feather": Does User Homophily Impact Information Diffusion in Social Media? <i>arXiv preprint arXiv:1006.1702</i> . https://doi.org/10.48550/arXiv.1006.1702
8	Peng, S., Yang, A., Cao, L., Yu, S., & Xie, D. (2017). Social influence modeling using information theory in mobile social networks. <i>Information Sciences</i> , 379, 146-159. https://doi.org/10.1016/j.ins.2016.08.023
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