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Measuring Social Influence in Online Social Networks - Focus on Human Behavior Analytics

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ABSTRACT

With the advent of online social networks (OSN) and their ever-expanding reach, researchers seek to determine a social media user's social influence (SI) proficiency. Despite its exploding application across multiple domains, the research confronts unprecedented practical challenges due to a lack of systematic examination of human behavior characteristics that impart social influence. This work aims to give a methodical overview by conducting a targeted literature analysis to appraise the accuracy and usefulness of past publications. The finding suggests that first, it is necessary to incorporate behavior analytics into statistical measurement models. Second, there is a severe imbalance between the abundance of theoretical research and the scarcity of empirical work to underpin the collective psychological theories to macro-level predictions. Thirdly, it is crucial to incorporate human sentiments and emotions into any measure of SI, particularly as OSN has endowed everyone with the intrinsic ability to influence others. The paper also suggests the merits of three primary research horizons for future considerations.

Keywords: *Social Influence Score, Influence Theories, Social Influence Measurements, Social Influence Behavioral Theories, Social Influence Models, Online Social Network, Social Influence in Online Social Networks*

INTRODUCTION

Humans gravitate toward ideas that are similar to their own, leading to influencing behaviors (Gladwell, 2002). They willingly adhere to individuals whose viewpoints align with their motivating opinion leadership (Chaudhry et al., 2013). Influence is accidental or unintended, as opposed to persuasion, which is typically intentional and requires some awareness of the target (Schiffer, 2001). American Psychology Association[1] dictionary defines SI as "any change in an individual's thoughts, feelings, or behaviors caused by other people, who may be present or whose presence is imagined, expected, or only implied." Any process by which social communication modifies or regulates a person's attitudes, opinions, beliefs, or conduct is referred to as SI by Oxford[2]. Human cultures are rife with SI. Obedience, compliance, persuasion, social loafing, social facilitation, observer effect, bystander effect, and peer pressure are all a wide variety of forms (Izuma, 2017). SI draws a connection to such human psychological phenomenon (Petty et al., 1986) resulting from endogenous diffusion (Valente, 1996) involving the transmission of attitudes, opinions, or actions within a social network. When averaged judgments contrast individual judgments, social groups can be surprisingly intelligent and knowledgeable. As a result, expert opinions tend to sway the masses (Dong et al., 2006). The emphasis is on possible changes in a person's behavior due to exposure to and contacts with others (Simon et al., 1998).

Despite increased demand, it can be argued that there is a lack of a reliable model to measure SI in OSN. Several academic research has sought to characterize influencing behaviors in concrete measurements (Alp et al., 2018) and how they might be represented to permit measurement within OSN (Huang et al., 2020); nonetheless, the results have been fragmented. Only a few researchers have attempted to architecturally depict the human behavior-influencing qualities in a network (Chen et al., 2012; Peng et al., 2017), but these efforts have not been grounded in established psychological theories. Lee et al. argued for an alternative theory focusing on informational SI and concluded through experimentation that it played a moderating role rather than the anticipated direct role in consumer behavior (Lee et al., 2011). Even commercial products like PeerIndex[5], Twitter- grader[6], and Kred[7], which quickly mushroomed to cater to the demand, strive to discover and engage with influencers with high social capital ranking scores to benchmark social media influence. Still, none have successfully created a comprehensive cognitive measure. This study will examine the many metrics, 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 characteristics that play a role in under-standing the influence behavior of social media users?
> **RQ2:** How do behavior theories manifest in measuring SI in OSN? What comprehensive approaches, metrics, and methods are prevalent in existing studies?
> **RQ3:** Are inter-twined behavior analytics capturing human sentiments represented comprehensively in measuring SI in OSN?

By examining the previous research and explicitly focusing on meticulous cataloging, this study adds exhaustive reference knowledge to the discipline and an extensive assertion of emerging issues, approaches, and concepts to guide research and improve related studies in the future.

MOTIVATION

Social media is only getting more potent as a medium of communication and entertainment, which means social platforms are becoming more consequential as their memberships grow exponentially, creating an opportunity for SI to take on a central stage (Granovetter, 1978).

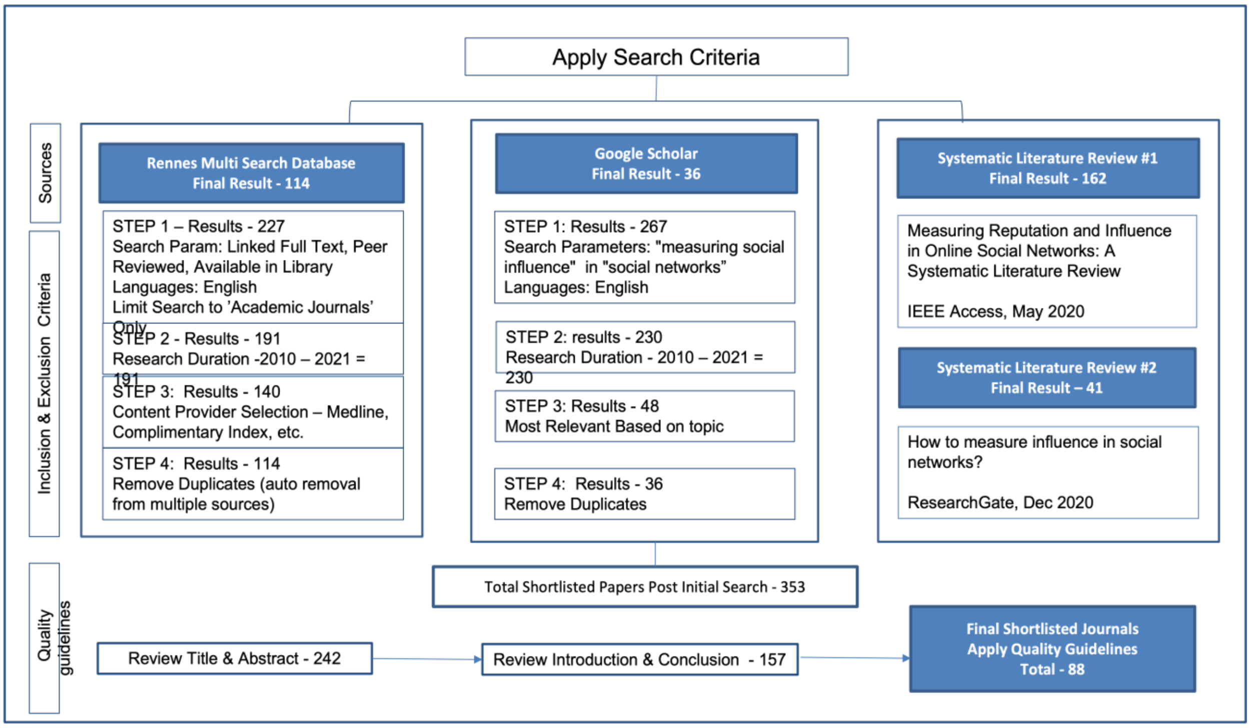
The marketing domain has undeniably taken the headliner, seizing advantage of the massive opportunity and propelling it to extraordinary popularity. The sector has gained considerable traction in adapting to SI strategies (Diba et al., 2019), including consumer buying decisions (Sridhar et al., 2012), viral marketing (Leskovec, 2007), product evaluation (Cohen et al.,1972), travel purchase (Tanford, 2015), shopper behavior (Zhang et al., 2014), and recommendation systems (Guo et al., 2016; Pálovics et al., 2014). Several popular hypotheses suggest that social support improves health by encouraging good behavior (Fowler et al., 2009). Indeed, research has linked SI to better medication adherence, higher physical activity, improved diet, and low- to-moderate tobacco and alcohol use (Christakis et al, 2007). Doctors and humanitarians rely on SI to promote healthy societal behaviors (Karelina et al., 2011). Similarly, SI dominance is understood to spontaneously presume an on-off disposition in a digital environment (Simon et al., 1998), spreading rumors (He et al., 2015). Contagion studies focus on controlling the rapid influence of OSN (Loersch et al., 2008). SI also pervades cultural markets, adopting scientific and technological advancements and disseminating social practices, including influencing economics, stimulating financial turbulence (Avery et al., 1998), and swaying voting behavior (Lazarsfeld et al., 1968).

SI’s infinite dependencies span business economics, social welfare, cultural evolutions, generational attitudes, political movements, and many more. Societies can steer and manage through significant transitions with the knowledge of influencing factors. Understanding social influence will also aid individuals in forming behaviors and influencing strategies that would likely produce the outcomes they were striving for. A cognitive SI measuring scale will allow individuals and corporations to reward the right influencing behaviors. As OSN is becoming the norm for societies to transact, establishing a standard similar to credit scores will introduce much-needed governance and regulations for monetizing individuals’ influence potential.

REVIEW METHOD

Although this study focused on selected works of literature, the rigor of a structured literature review (SLR) (Brereton et al., 2007) was applied. As depicted in Figure 1, the goal was to exhaustively identify all relevant studies in the field, assess their importance, and synthesize the conclusions that would address the research. The study further distinguishes associations, commonalities, repudiations, gaps, and discrepancies in the literature to provide practical implications (Unterkalmsteiner et al., 2012).

Figure 1. PRISMA Approach to Focused Literature Review



Section 4 presents the human behavior characteristics that impact human influence and associated psychological theories. Section 5 discusses the challenges and limitations of the current studies based on the examination report of this exhaustive research of 88 shortlisted papers through the lens of the twelve categories of psychological theories. Section 6 suggests unique approaches with directions for future study, and section 7 wraps up this research with a succinct conclusion.

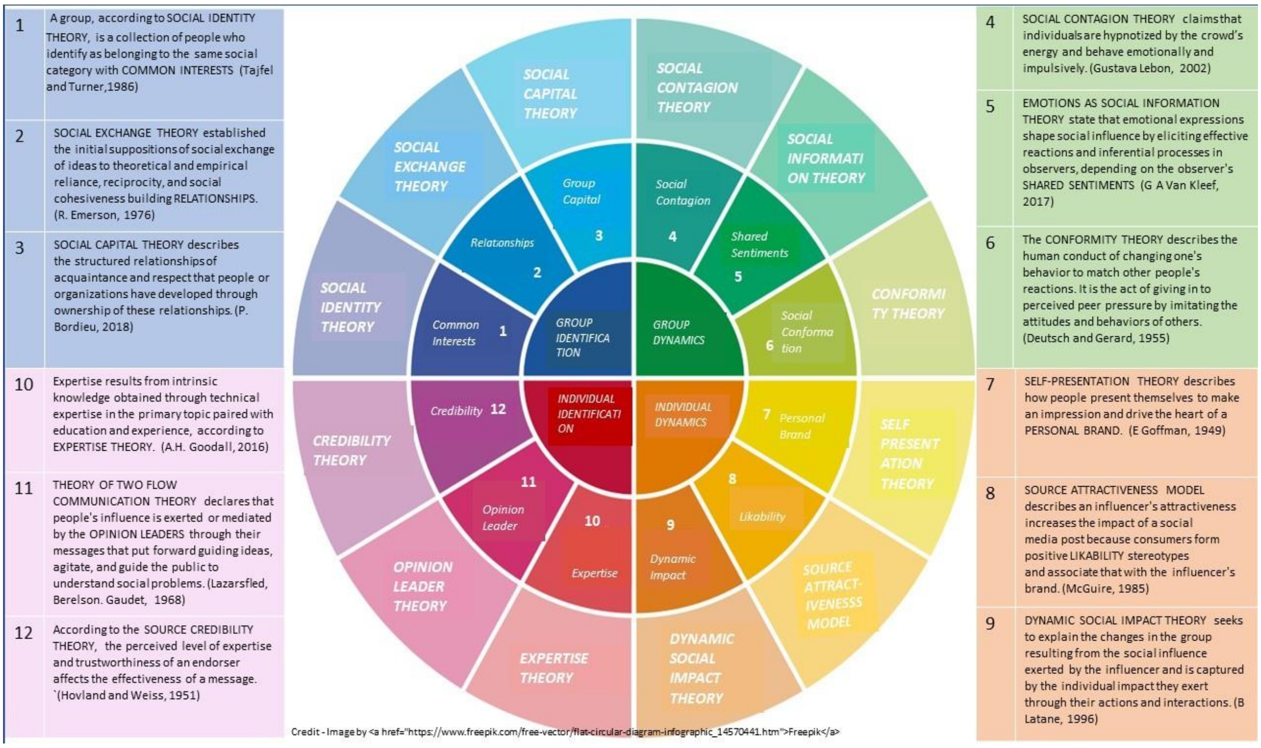
BEHAVIOR-BASED FEATURES IN MEASURING SI IN OSN

Social psychology studies how people behave in social interactions and how various contextual elements interact (Nisbett and Ross, 1991). SI is a general term that covers a wide range of phenomena; thus, we have consulted twelve relevant psychological theories, that introspect both group and individual human behaviors, as depicted in Figure 2. Understanding these human behavior traits can provide further directive and a structural representation to cognitively represent this phenomenon in OSN to create a tangible measure of SI.

Common Interests within a Network Group

In an age of information overload, filtering based on common interests will assist people in inferring the information they are ultimately interested in (Dietz, 2010) prompting several studies to understand how common interests impact social influence. Rapid accumulation of common interests leads to trust in relationships (Ji et al., 2015) leading to increased influence. Social identity theory defines a group as a collection of individuals who identify as members of the same social category and share similar interests. They frequently internalize the social identity, defining characteristics to emphasize intra-group similarity and inter-group difference (Tajfel and Turner, 1986).

Figure 2. SI Through the Lens of Human Behavior Theories



Influencer Relationships within a Network Group

As Carnegie[8] puts it, "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. Correlations in behavior could be brought about by homophily (Mcpherson et al., 2001). One of the most influential theories of social interaction in the social sciences is Social Exchange Theory by Homans, Blau, and Emerson. Power and dependence, social networks, reciprocity, social cohesion, and solidarity are among the theoretical and empirical discoveries resulting from their work (Emerson, 1976).

Influencer Social Capital within a Network Group

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, 2015). People with high social capital are considered to be highly influential. Social Capital Theory is most simply defined as features of social context that offer productive advantages (Bourdieu, 2018). Bourdieu described social capital as "more or less institutionalized relationships of mutual familiarity and recognition" that individuals or organizations had accrued through time (Julien, 2015).

Social Contagion within a Network Group

Spontaneous transmission of traits, sentiments, or disorders within a network is organically referred to as contagions (Levy, 1993). Since the late 19th century, social scientists have studied the phenomena, albeit precise definitions have varied because most of the research on the topic was based on ambiguous or contradictory ideas. Some academics classify the unintended transmission of ideas among a population as social contagion, while others narrow it down to the spread of pretense (Goldstone, 2005). Gustave Le Bon, a French philosopher, created the Contagion Theory in his seminal work, "The Crowd: A Study of the Popular Mind," in which he claimed that people behave rationally while alone but get practically hypnotized by the influential energy of a crowd and behave emotionally and impulsively (Bon and G, 2002). Individuals exhibit irrational and sometimes even vicious acts as they lose control of their unconscious instincts (Le Bon, 1896). Collective behavior is emotional and mostly irrational and results from the crowd's hypnotic influence, resulting in echo chambers on the OSN (Christakis and Fowler, 2013).

Shared Sentiments within a Network Group

As Dr. Simon[9] noted, sentiments and emotions affect, distort, and sometimes entirely dictate the result of a significant number of decisions we face each day. 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 social influence by eliciting effective reactions and inferential processes in observers (Van Kleef, 2017).

Social Conformation within a Network Group

Conformity is the act of altering one's behavior to suit the responses of others. Deutsch and Gerard divided this further into informative and normative behaviors, with the former based on the need to develop an accurate perception of reality and the latter on the need to win others' approval (Deutsch and Gerard, 1955). Cialdini and Goldstein examine the conformity theory as the foundation of a target's receptivity to external influences to reward human cognition (Cialdini and Goldstein, 2004).

Influencer Personal Brand

The personal brand and the charisma of the influencer play a critical role in determining their influencing ability. Celebrity endorsers are used by marketers in anticipation that their fame will propagate the brand's image or product (Erdogan, 1999). Self-Presentation Theory, developed by Erving Goffman, 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 (Goffman, 1949).

Influencer Likability

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. 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." (Li et al., 2018). By definition, attractiveness creates an emotional connection between its supplier and recipient. In other words, when someone wants to identify with the source, they are more likely to be influenced by it and more inclined to identify with likable persons (Kelman, 1961).

Influencer Dynamic Social Impact

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 (Oc et al, 2013). Miller et al. looked at the Social Impact Theory to better understand the origins and goals of interpersonal influence during network-generated interactions (Miller et al., 2008). They discovered that exaggeration and assertiveness were the two behavior qualities that significantly contributed to influence as compared to emotional intensity and sensitivity. Latane's Social Impact Theory is based on the idea that society is a complex, self-organizing system comprised of interdependent individuals who abide by basic social impact principles (Latane, 1981). A person's susceptibility to social influence depends on the group's strength, proximity, and size (Latane et al., 1996).

Influencer Expertise

Expertise is widely regarded as the most critical social attribute to 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 (Cambridge University Press, 1991). The Expertise Theory as defined by Goodall provides us with the foundation for this human behavior. Expertise in a domain comes through inherent knowledge and craft fully acquired technical and business acumen (Goodall, 2016).

Influencer Opinion Leadership

People often become opinion leaders when they provide helpful interpretations of daily life and current events that help others, mainly when important events occur. Therefore, locating them helps us identify the influencers. The foundation for opinion leadership origination is provided by the two-step communication flow hypothesis presented by (Paul Lazarsfeld and Elihu Katz, 1968). 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 (Jungnickel, 2018).

Influencer Credibility

Credibility may be traced back to Aristotle's Rhetoric theory. Rhetoric, according to Aristotle, 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 and naturally influenced when the source appears credible (Hovland and Weiss, 1951).

DISCUSSIONS ON LIMITATIONS AND GAPS

Academics are increasingly interested in understanding human behavior traits, so appropriate measures can be accounted for people's innate propensity to be influenced by emotions when creating a measure of SI.

1) It has proven challenging for psychologists and human behavior analysts to define these twelve characteristics of human conduct concisely, let alone examine them thoroughly through the prism of an individual's influencing power.
2) We can't ignore collective human behavior when the psychological elements of each individual characteristic intertwine as humans act and react to various scenarios in social media.
3) Everyone now has the intrinsic ability to create content on social media platforms, which opens up the possibility of being an influencer. It has been hard to decipher and encapsulate the feelings and sentiments expressed in OSN into a tangible measure.
4) Another obstacle has been depicting these behavioral characteristics as a quantitative cognitive component within any OSN. The several emerging perspectives due to the innate characteristics of social media cannot be ignored.

Lack of Proven Psychological Perspectives

The most significant shortfall we see is the lack of consideration of psychological theories tied to an in-depth understanding of human behaviors while considering a definition of influence measure. For instance, few social media analysts conclude that people with common interests tend to organically associate themselves. So, tracking user interests (L.L. Shi et al., 2017) and shared content interests (Abu-Salih, 2020) amongst the network group will provide a good measure of social influence. DSUN (Dynamic User Networking Model) by Zhou et al. accommodates a similarity-based representation of common interests with topic-aware traits and an influence-based representation of explicit relationships based on behaviors (Zhou et al., 2018) providing an opportunity to capture the dynamics of OSN. However, these researchers measured common interests by topological features such as overlap rates, taste similarity, and user degree ranking. To our knowledge, no meaningful study examines the psychological theories that govern common interests as a credible means of influence.

Similarly, the influencer relationship has been studied to identify the influencing potential of a social media user (Anagnostopoulos et al., 2008). Studies enable estimating a user's influence within a community through rigor in tracking changes to user relationships based on the domain-centric topic of conversations (Cataldi et al., 2013, Ma, 2017), content sharing through unidirectional relationships (Z. Shi et al., 2014), or user's placement in the social network and their relationships with fellow users (Smailovic et al., 2018). While Romero et al. offered an all-encompassing model of influence based on the notion of inactivity or passiveness in a social network (Romero et al., 2011), understanding the impact of human relationships on influence is thus far confined to calculating based on user similarity, and that is too limited to key relationships. Additionally, the measure is unidirectional, even when calculating influence based on key relationships.

Numerous studies postulate that people with substantial social capital are frequently key network influencers (Badawi et al., 2019) offering evidence of the significance of the relationship between one's social capital and their influencing ability (Subbaian et al., 2014; Dugue et al., 2015). Data-driven generalized impact models have been introduced to examine the distribution and diffusion of this feature through networks as a primary approach to measuring influence (Ram et al., 2021; Danisch et al., 2014). While it is promising that these studies have discovered a connection between a person's social capital and capacity for influence, there is a severe shortage of knowledge regarding human psychology that may help develop more accurate measures of influence.

The understanding of the impact of social contagion on influencing abilities has only been explored in a relatively small number of research that did so more accidentally than intentionally (X. Li et al., 2018; K. H. Kwon et al., 2014). Due to the exponential rise of OSN caused by "network effects," it is now even more important for academics to consider the consequences of social contagion. Given that the human tendency to conform to social norms is a tenured concept, numerous studies have been conducted to represent this complex phenomenon in OSN. Li et al. created a revolutionary conformity-aware cascade model CINEMA (Li et al., 2015) to find ways to maximize influence and later enhanced this model to CASINO, which improved efficacy and accuracy (Li et al., 2017). These attempts have significantly contributed to creating a meaningful measure, however, there is an opportunity for a comprehensive structural investigation to view human nature to conform within the context of correlated behaviors to form a robust measure of SI.

Celebrity endorsement has been a traditional marketing technique. Studies have paved the way to assess an influencer's brand strength based on their social media engagement, relevancy, and high financial impact (Faliagka et al., 2018). Algorithms such as 'TUrank', which uses the 'ObjectRank' link-based approach to identify followers, have gained prominence in evaluating users' authority ratings (Taillon et al., 2020). While celebrity endorsement has long been prevalent in influencer marketing, present methodologies focus primarily on the influencer syndrome, limiting themselves to generic expertise and common branding techniques. It is worth examining this human behavior around personal branding based on the psychological theory foundation for the translation, interpretation, and measurement of SI on OSN.

People's willingness to comply with requests was allegedly influenced by the social in- fluence principles of likability and interpersonal validation, especially in online environments (Guadagno et al., 2013). Beauty predicts favorable sentiments toward the influencer word-of-mouth, whereas similarity predicts follower word-of-mouth. Thus, the effect of likability on attitude toward the influencer is mitigated by proximity (Taillon et al., 2020). Mei et al. applied the principal component analysis, rank correlation analysis, and stepwise multiple linear regression algorithms on Twitter data to identify that popularity is the leading human trait that creates influence followed by engagement, and authority (Mei et al., 2015). Qasem et al. quantify an actor's social influence as the power with which an actor may entice other significant actors into a networked community (Qasem et al., 2017). Although the model provides a generic framework, it does not offer a comprehensive perspective of this human behavior which deserves additional research.

Most emerging studies are around understanding the dynamic social impact created by a social media user. Difonzo et al. identified that group-level characteristics like cohesiveness and follower count matter along with individual factors of an influencer, such as strength and availability (Difonzo et al., 2011). Tanford and Penrod provide proof of the key tenet that claims that the first influence source always has the greatest impact (Tanford et al., 1984). Given that social impact influences behavioral changes, irrational experiences, and emotions exerted through acts and interactions (Latane 1996), a theoretically informed intrinsic evaluation is essential in determining the SI measure.

Robust academic research, experiments, and surveys have been undertaken to understand how experts impact society and, more crucially, how expertise influences an influencer's capacity to persuade their followers on OSN (Liu et al., 2012), the extent of the relationship between expertise and influence that exert influence even outside of their area of expertise (Zhao et al., 2014). With social media enabling everyone to become content generators, influence based on expert content created through microblogs at topic levels across the heterogenous networks has been well studied (Hamzehi et al., 2016; L.L. Shi et al., 2017; Liu et al., 2012; Tang et al., 2009; Zhaoyun et al., 2013). 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 (Ericsson et al., 2012).

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 grows in OSN (Rogers et al., 1962). It is encouraging to see that few studies have focused on using 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 (Bergsma et al., 2014, Oro et al., 2018; Afridiana et al., 2019). Jungnickel has completed an exhaustive systematic literature review that can provide an opportunity to review the measures more wholistically (Jungnickel, 2018) to create a comprehensive measurement metric.

Increased communication on a diverse set of topics builds credibility (Huffaker, 2010). Researchers have shown interest in the "mind economy" (Khrabrov et al., 2010), identifying people with rising influence based just on the format and tempo of their conversations (Alrubian et al., 2022). Trustworthiness is the quality that consumers found to be most compelling (Wang et al., 2018). Wiedmann and Von Mettenheim's study looked at how success criteria were more closely tied to influencers than to the information in their profile to demonstrate the importance of credibility and trustworthiness. (Wiedman et al., 2021). Academics should not only have a genuine interest in understanding the impact of credibility but also explore the interconnectedness with trustworthiness and related innate psychological behavior traits to get an accurate measure of SI.

Stagnation in forming a collective definition

As we thoroughly examined the shortlisted research works, the studies have restricted themselves to viewing influence definition from just one or few human characteristics, choosing the theory or rhetoric most convenient or easily transferable to a measurement scale. For instance, some social behavior analysts conclude that consumers' perceptions of an influencer's likability (Guadagno et al., 2013; Taillon et al., 2020), social capital (Badawi et al., 2019; Dugué et al. 2015; Gladwell, 2002; Ram et al., 2021), or personal brand (Faliagka et al. 2018; Taillon et al. 2020), increases purchase intention toward endorsed brands thereby proving social influence. Whereas a few other researchers focused on the social norms of conformity (K. H. Kwon et al., 2014; Lorenz et al., 2011; Muchnik et al., 2013), the innate nature of building relationships (Cataldi et al., 2013); Ma, 2017); Smailovic et al., 2018), or common interests (Ji et al., 2015), L. L. Shi et al., 2017; Zhou et al., 2018) as the key drivers. The behavior illuminations across the connected character traits such as credibility (Alrubaian et al., 2022; Hovland and Weiss., 1951; Khrabrov and Cybenko, 2010), influencer expertise (Liu et al. 2012); Zhao et al. 2014), or opinion leadership (Jungnickel, 2018; Rogers and Cartano, 1962) each adding their own dimensional to the social influence connotation, makes it even harder to arrive at a robust common definition. The disjointed definitions of measurements of human behaviors are the major constraints on present research. The complexity further intensifies as these individual behaviors intertwine in social media (Miller et al., 2008). OSN is susceptible to the spontaneous transmission of features, attitudes, or ailments (Lev et al., 1993) within a network that needs to be accounted for (Le Bon, 1896). Group-level characteristics matter along with the individual traits of an influencer (Difonzo et al., 2011) to account for social impact behavioral changes, illogical experiences, and emotional reactions brought on by human interactions dynamic changes in OSN (Latane, 1981).

Everyone is an Influencer

Aristotle claimed that the speaker's dependability must be formed and established in speech and that what the speaker did or said before such a speech was irrelevant (Zeller, 1897). A few studies took this definition of credibility as a basis of influence measurement (Alrubaian et al., 2022); Khrabrov et al., 2010; Wang et al., 2018) as it removed the burden of understanding the full context of the speaker. While celebrity endorsements are well-known for influencing consumer goods, content specialists are frequently used to influence technical products or complex scientific and socioeconomic phenomena. Zhao et al. research discovered a tangible link between degrees of competence and social media impact ratings, proving that expertise is critically compared to relevance and participation (Zhao et al., 2014). Several academics have established the importance of topic-based content analysis (Hamzehei et al., 2016) across heterogeneous (Liu et al., 2012), large-scale social networks (Tang et al, 2009), micro-blogging sites (Zhaoyun et al. 2013), and data streams (L. L. Shi et al., 2017). While it may be challenging to locate these influencers, it is undeniable that consumers are turning to them for advice when making purchasing decisions. With the proliferation of social media, brands have more potential with macro- influencers[10] as they generate between 5% and 25% of engagement and micro-influencers[11] who generate 25% and 50% of engagement[12]. Today, consumers are more likely to believe recommendations from real-life personalities than follow a brand's celebrity endorsements uncritically. As society greatly adapts to digital and social media, it is the right time for researchers to define a measure to identify and tap into this intrinsic influencing ability that would span beyond marketing.

Quantifying human emotions

Social relationships are anchored on trust and shared goals within a group or network. Given the significance of relationships in understanding influence, academics have been interested in learning how relationships are represented (Anagnostopoulos et al., 2008) and measured (Cataldi et al., 2013; Ma, 2017; Smailovic et al., 2018) in OSN. Studies have tried to quantify influence based on the followers' positive and negative reactions to the stimuli depending on the influencer's perception and credibility (Bae et al., 2012). Scholars have attempted to create a topic-based sentiment score (Alrubaian et al., 2017) and a cumulative scoring model based on engagement, outreach, sentiment, and growth attribute (Arora et al., 2019). Servi and Elson introduced a novel method by devising a quantitative technique for text processing and coupled it with a statistical algorithm to find patterns in emotions which was a significant departure from just using links or tweets (Servi et al., 2014).

The proposed influential model by Meeker in 1971, based on the social exchange theory, argues that interpersonal exchanges can be treated as individual decisions (Meeker, 1971). However, the quandary is that it is impossible to assess the broader emotional connection between the influencer and their audience (Ferrara et al., 2015). Irony permeates many online writings, making its detection more challenging due to the lack of in-person interaction and vocal inflection. It will only become increasingly tricky as humans adapt to the metaverse[13]. As OSN is becoming a common medium for people to share information, symbols, and emoticons are becoming very popular. Sun and Ng aimed to assess the effect of a post are favorable or negative emotions through a comprehensive vocabulary model dealing with symbols and emoticons (Sun et al., 2014). While it was a great start, they could not continually maintain classification given the rapid growth in the number of emoticons and memes. Sentiment research must go beyond words because social media users rapidly adopt 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 (Gleick, 2011). Since they are flexible and respond rapidly to changing conditions, 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; News, 2014). They are significant in Western and Global cultures (Fisher, 2015). The Face with Tears of Joy emoji (😂) was selected by Oxford Dictionaries as the word of the year for 2015 (Kelly, 2015).

DIRECTIONS FOR FUTURE STUDY

The study's exploratory and interpretive nature presents many possibilities for further investigation of the theory progression and concept confirmation.

Merits of Modeling Approach

It makes sense to continue investigating, improving, and, more importantly, testing the efficacy of behavior modeling to represent social influence theories. Agent-Based-Modeling (ABM) lends itself to simulating and validating behavior theories (Bankes 2002; Rao et al., 1995). In a very unique attempt by Van Maanen et al. (2014), Cialdini's model of social influence (Cialdini, 2001) is simulated using the dynamic application of Agent-Based-Modeling (ABM) (Van Maanen et al., 2014). Using a Dutch television show as a use case, they demonstrated the ability to model social influence backed by strong psychological theories (Maanen et al, 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 and efficacy to social behavior modeling. While ABM is versatile and diverse, understanding design and rigor around arranging the components into Properties, Actions, Rules, Time, and Environment (PARTE) are critical to success. 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 social influence.

Merits of AI and Deep Learning Tools

It is vital to capitalize on deep learning advancements to capture influence across multiple social networks or NLP to accentuate shared sentiments. Scholars have expressed increased interest in taking advantage of the growing art of the science of machine learning algorithms to represent and measure human behaviors in OSN (Tang et al. 2009; Cataldi et al. 2013). The theoretical framework based on dual-process and social influence theory (SIT) was conceptualized by Kwon et al., in which they empirically investigated a significant amount of customer review data (Kwon et al., 2021). Although this cutting-edge neural network model is up-and-coming, it faces two common problems, as with any deep neural network: interpretability and scalability. There is an opportunity to examine human behavior-based traits and discover an equivalent system model to express and quantify them in OSN (Guimerà et al., 2005).

Merits of Sentiment Analytics

The user's social influence depends on how popular and emotional they are about a specific topic. The user's engagement, outreach, sentiment, and growth attributes determine the impact on the users. Sentiment influences perception, credibility, and how individuals respond to such stimuli (Van Kleef, 2017). Academics are increasingly interested in how user sentiments and emotions about a topic or issue affect influence; nevertheless, there is a lack of knowledge of psychology behind people's inherent proclivity to be influenced by emotions (Zhang et al., 2018). The difficulty of creating a classifier from the text has to be conferred while discussing sentiment analysis (Bae et al., 2012). A lexicon of emotional phrases can be used to count the words, classic classifiers like logistic regression can be fitted to word counts, or, most recently, powerful neural networks can be used (Ferrara et al., 2015). These techniques gradually enhance classification at the expense of more work and less clarity. Sentiment research must go beyond words and phrases because social media users are now rapidly adopting memes, emojis, and emoticons. Researchers must weigh influence against the sentiment analysis industry's expanding interest.

CONCLUSION

Finding pertinent academic and scientific data to analyze and synthesize viable metrics to measure SI in OSN was the main objective of this focused literature study. While methodological flaws and restrictions were the main focus, we also looked at the merits of further research by highlighting links, paradoxes, and inconsistencies in the literature and adding justification for a few different approaches. The above-documented result comes from an extensive evaluation that identified relevant theories, evaluated the content in light of psychological characteristics, and assessed methodologies for their value and applicability.

This paper significantly advances the field of study by compiling the most recent academic research on the social impact of social media networks. Further accelerating the study to create a cognitive measure for SI in OSN will facilitate the expansion of monetizing a person's social influence and, more significantly, assist the influencer in seeing the value of their social influence.

Foot Notes

[1]APA - The American Psychological Association is the largest scientific and professional organization of psychologists in the United States.

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

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

[5]PeerIndex - PeerIndex is a web technology company that enables you to learn about the influence of social media platforms

[6]Twitter Grader - Twitter Grader is a free tool that analyzes and measures users' Twitter profiles for marketing purposes

[7]Kred - Kred is a score and a platform for increasing your Online Influence.

[8] Dale Carnegie -November 24, 1888 – November 1, 1955) was an American writer and lecturer.

[9]Dr.Herbert Simon - Nobel Laureate

[10]macro Influencers - 10K to 10M followers; micro-influencers - 500 - 10K followers

[11]macro Influencers - 10K to 10M followers; micro-influencers - 500 - 10K followers

[12] Influencer Marketing Challenges Brands Face (+ How to Solve Them) - https://influencermarketing hub.com/influencer-marketing-challenges/

[13]Metaverse is an iteration of the Internet as a single, universal, and immersive virtual world

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