Social Media Influencers- A Review of Operations Management Literature

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

This literature review provides a comprehensive survey of research on Social Media Influencers (SMIs) across the fields of SMIs in marketing, seeding strategies, influence maximization and applications of SMIs in society. Specifically, we focus on examining the methods employed by researchers to reach their conclusions. Through our analysis, we identify opportunities for future research that align with emerging areas and unexplored territories related to theory, context, and methodology. This approach offers a fresh perspective on existing research, paving the way for more effective and impactful studies in the future. Additionally, gaining a deeper understanding of the underlying principles and methodologies of these concepts enables more informed decision-making when implementing these strategies.

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Dedication

This thesis is dedicated to my aunt Lindy. May her soul rest in eternal peace.

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Chapter 1

Introduction

An influencer is an individual who attracts the attention of many people (also known as followers) on social media and whom these followers entrust as a source of advice. It can be anyone who reviews products, posts a blog about new products, has the potential to influence people or is an industry expert [325]. Across various domains of industry and academic research, these influential individuals are often referred to as seeds [159, 167, 309], nodes [133], influentials [24, 441], opinion leaders [72, 149, 152, 231, 271, 296, 331, 403, 415, 453], market mavens [425], hubs [176] and/or influencers [289, 325, 424]. Some authors even explore their characteristics further by claiming that they assume specific roles such as product enthusiasts [56], early adopters [34, 130, 132], experts and high reputation informants [217, 331] and celebrities [98, 245, 258, 267].

In 2022, influencer marketing grew to an estimated market size of $16.1 billion and is projected to increase by 29% to $21.1 billion in 2023 [228]. Influencer recommendations positively impact consumer purchasing behaviour [93, 131, 144, 151, 180, 194, 300, 326, 366, 445]. As such, companies continue to invest a large proportion of their marketing budget into influencer marketing to target potential consumers [288, 289, 313].

Analogous to the upsurge of social media influencer marketing among practitioners, a surging body of literature exists to explore the phenomenon. Numerous literature reviews have emerged, focusing on the theoretical aspects of influencer notions and consequent follower behaviour [141, 249, 400, 401, 424]. Specifically, how the behaviour of influencers and the content they share affect the attitudes and behaviour of those who follow them, especially with regard to purchasing goods and/or services.

Influencer maximization and seeding strategies are two pivotal concepts in influencer marketing and social network analysis. Numerous literature reviews provide a comprehensive and critical analysis of the existing research on methods and algorithms used to solve the influence maximization problem [28, 33, 237, 377, 393]. These reviews explore the different types of network models used, the algorithms and heuristics employed to identify influential individuals, and/or the evaluation metrics used to measure the effectiveness of these methods. Likewise, there are analyses of the existing research on seeding strategies which cover topics such as the different types of seeding strategies used, the various metrics employed to measure the effectiveness of these strategies, and the factors that influence the success of a seeding campaign. Typically, these papers are highly specific and focus on a single strategy while exploring certain conditions. This is then complemented by an overview of the studies most relevant to the topic being examined. For example, to complement his investigation into how follower count (indegree) affects social media engagement, [446] analyzed empirical studies of indegree seeding strategies and summarized their findings. [213] conducted an empirical comparison of four seeding strategies and then recommended the most successful approach. To this end, we have not been successful in finding a stand-alone literature review of a broader scope of seeding strategies.

Our paper offers a comprehensive view of the seeding and influence maximization literature that goes beyond the usual recommended strategies and modelling survey. Taking a unique approach, we focus on the research methods used by authors to arrive at their conclusions, including experiments and network analysis. By zooming out, we provide a critical analysis of both the seeding and influence maximization literature in a single paper, offering a wider view than existing literature reviews on individual topics. Our value proposition lies in offering a new perspective on existing research and providing insights that can lead to more effective and impactful research in the future. Moreover, a deeper understanding of the underlying principles and methodologies of these concepts allows for more informed decision-making as it pertains to implementing these strategies. It is important to emphasize that our study focuses specifically on the fields of management science, production and operations management, marketing science, management, operations research, economics, and social science. This distinction is significant as it sheds light on studies that are often overlooked in literature reviews that tend to be dominated by marketing journals.

The paper is structured as follows: We first elaborate on our review methodology in chapter 2 which includes the data selection in section 2.1, data coding in section 2.2 and limitations in section 2.3. Then in chapter 3, we offer a descriptive analysis of our findings, which is thematically classified into four sections. In section 3.1 of our thematic analysis, we acknowledge that influencers have revolutionized traditional marketing and are an important marketing tool. In this section, we also discuss the similarities and variations among studies highlighting the proliferation of SMIs in marketing. In section

3.2, we discuss the seeding strategies used to select them, focusing on the methods used to propose such strategies. This chapter is comprised of two subsections: (3.2.1) network seeding which is associated with information propagation and (3.2.2) product seeding which is fundamentally new product adoption via opinion sharing. In section 3.3, we address influence maximization which involves spreading a marketing message via the selected individuals to as many people in the network, as quickly as possible. There is a subsection 3.3.1 on profit maximization which entails identifying a subset of individuals in a network to maximize profit while maximizing information spread through the network. In section 3.4, we discuss how influencers have been used in society to spread marketing messages in fields such as health care, education, policy, retail and supply chain. Finally, in chapter 4, we conclude and propose future research directions.

Chapter 2

Methodology

This chapter provides a thorough account of our research methodology in creating an extensive synthesis of existing literature on SMIs. The chapter is divided into three distinct sections. Section 2.1 focuses on the data selection process, presenting a detailed overview of how we identified and chose the relevant data for our study. In section 2.2, we delve into the data coding procedures, outlining the specific methods and techniques used to analyze and interpret the gathered information. Lastly, section 2.3 sheds light on the limitations of our study, offering a critical examination of the constraints and potential weaknesses inherent in our research approach. By organizing the chapter in this manner, we aim to provide readers with a clear and comprehensive understanding of our research methodology and the key aspects of our study on SMI literature synthesis.

2.1 Data Selection

The following query string was entered into the Web of Science database: "influencer marketing" or "social media influencer marketing" or "social media influencer" or "digital influencer" or "online influencer" or "online opinion leader" or "seeding" or "viral influencer" or "social network" or "social media". Using the same query string in Google Scholar produced an error message with no results. Therefore, we entered each term one at a time in the database and did individual searches. This produced 315 results.

In the Web of Science database, we refined the sample by only selecting the journals of Management Science, Production and Operations Management, Marketing Science, Academy of Management Journal and the fields of Operations Research and Economics and Social Science. These fields and journals are pre-set categories under the "Publications/Source Titles" section in Web of Science. To maintain consistency, we manually filtered our Google Scholar results according to the aforementioned fields and journals by excluding any papers that were not published in those journals. This produced 110 results. After that, to ensure the quality and validity of our research, we screened the articles and only selected those published in journals included in the Financial Times' top 50 (FT50) journal list. Referencing academic papers from the FT50 journal list for an academic literature review provides several benefits, including ensuring the credibility and reliability of the sources used, as the FT50 journal list comprises reputable and well-established journals in various fields. Additionally, citing papers from this prestigious list enhances the academic rigour and validity of the literature review, as it reflects the utilization of high-quality and influential research within the scholarly community. We then reviewed the references of each paper and the articles which cited them. Reviewing the reference list of each paper and examining the articles that cited it is essential in an academic literature review as it helps to identify the foundational sources that have influenced the current research and provide a broader context for the topic. This allowed us to trace the evolution of ideas, track key contributions, and ensure comprehensive coverage of the relevant literature, enhancing the depth and credibility of our review. Finally, we reviewed each title and added all related papers to our list. This reduced our collection to 61 journal articles.

It is worth mentioning that this work is exploratory in nature. In conducting this comprehensive literature review, our attention was directed toward the fields of research and scholarly publications from which the utilized papers originate. This selection was guided by the understanding that these journals serve as the primary outlets for researchers within the operations management and management science discipline.

2.2 Data Coding

After the paper selection process which resulted in 61 journal articles, we read the abstracts of each paper and grouped them based on similar prevailing themes in the literature. The following themes were revealed: (1) the importance of SMIs in literature, (2) how to select influencers for marketing campaigns, (3) how to spread a marketing message to as many people as possible and as quickly as possible while minimizing costs, (4) how influencers and social media data are used in various ways in society and (5) how influencers strategically act and how followers react to this behaviour. However, after recognizing that the fifth theme was very saturated and was thoroughly examined in academic research [141, 249, 400, 401, 424], we decided to eliminate all the papers in this category, narrowed our scope and focus on the first four themes.

Subsequently, we read each paper in full and used a snowball sampling method to select material mentioned in each paper that was relevant to the four themes being investigated. This included book chapters, conference proceedings and dissertations. Thus, a more comprehensive understanding of each theme was garnered which facilitated a more extensive analysis of the overarching research field.

In writing this literature review, we curated the existing literature by ordering the four themes to tell a story about (1) the importance of SMIs in literature, (2) how to select influencers for marketing campaigns, (3) how to spread a marketing message to as many people as possible and as quickly as possible while minimizing costs and (4) how influencers and social media data are used in various ways in society. The batch of papers that talked about the importance of SMIs all pertained to their importance in marketing. Therefore, the first theme in the findings chapter was titled "Acknowledging SMIs as a Marketing Tool". The second batch of papers on how to select influencers for marketing campaigns related to two types of seeding strategies, network seeding and product. Therefore, I titled this theme "Seeding Strategies" with subsections for network seeding and product seeding. The third batch of papers about how to spread a marketing message to as many people as possible and as quickly as possible while minimizing costs focused on influence maximization and profit maximization strategies. As such, I titled this theme "Influence Maximization" with a subsection titled "Profit Maximization". The final batch of papers on how influencers and social media data are used in various ways in the society presented studies on the use of SMIs and social media data in specific applications such as healthcare, crisis communication, operations and supply chain management and policy. Therefore, I titled the final theme "Applications of Social Media and SMIs in Society" with subsections "Healthcare", "Crisis Communication", "Operations and Supply Chain Management" and "Policy".

2.3 Limitations

Firstly, two electronic databases were used to search for material relevant to our study. As a result, we may have missed some material relevant to our study found in other databases. Secondly, the query string and the filtering process used may not have covered the entire research landscape. Nevertheless, we believe that our search was validated by our thorough reference and citation checks along with a screening of each article for related work. We are confident that this meticulous search procedure allowed us to produce a high-quality literature review of SMIs from a management science perspective.

Chapter 3

Thematic Analysis

This chapter comprehensively reviews the existing literature on SMIs, presenting a four-part narrative. Firstly, it delves into how SMIs have revolutionized marketing, followed by insights into their recruitment and the efficient dissemination of marketing messages. Lastly, it examines their applications in various industries such as healthcare, crisis communication, supply chain, and policy, with a particular focus on the research methodologies employed to produce these findings. Figure 3.1 on page 8 illustrates the flow of chapter 3.

3.1 Acknowledging SMIs as a Marketing Tool

This section presents a comprehensive synthesis of research on SMIs as influential marketing tools [352]. Through an analysis of various studies, we offer valuable insights by highlighting both the similarities and differences across different research areas of SMI marketing. These insights were developed through the exploration of the impactful role of SMIs in brand communication, influencer marketing, and social media research. Our analysis of SMI literature identifies common themes such as the focus on SMIs in marketing campaigns, the importance of influence and credibility among SMIs, and the significance of brand value and social media in marketing are present. However, the same analysis identifies variations among opinions on the integrity and trustworthiness of SMIs in marketing campaigns, research and data collection methods used to examine SMIs, as well as the measuring techniques proposed to quantify influencer impact.

Numerous studies recognize the importance of SMIs in brand communication and marketing campaigns [28, 133, 165, 270, 352, 402, 423]. The proliferation of SMI marketing was

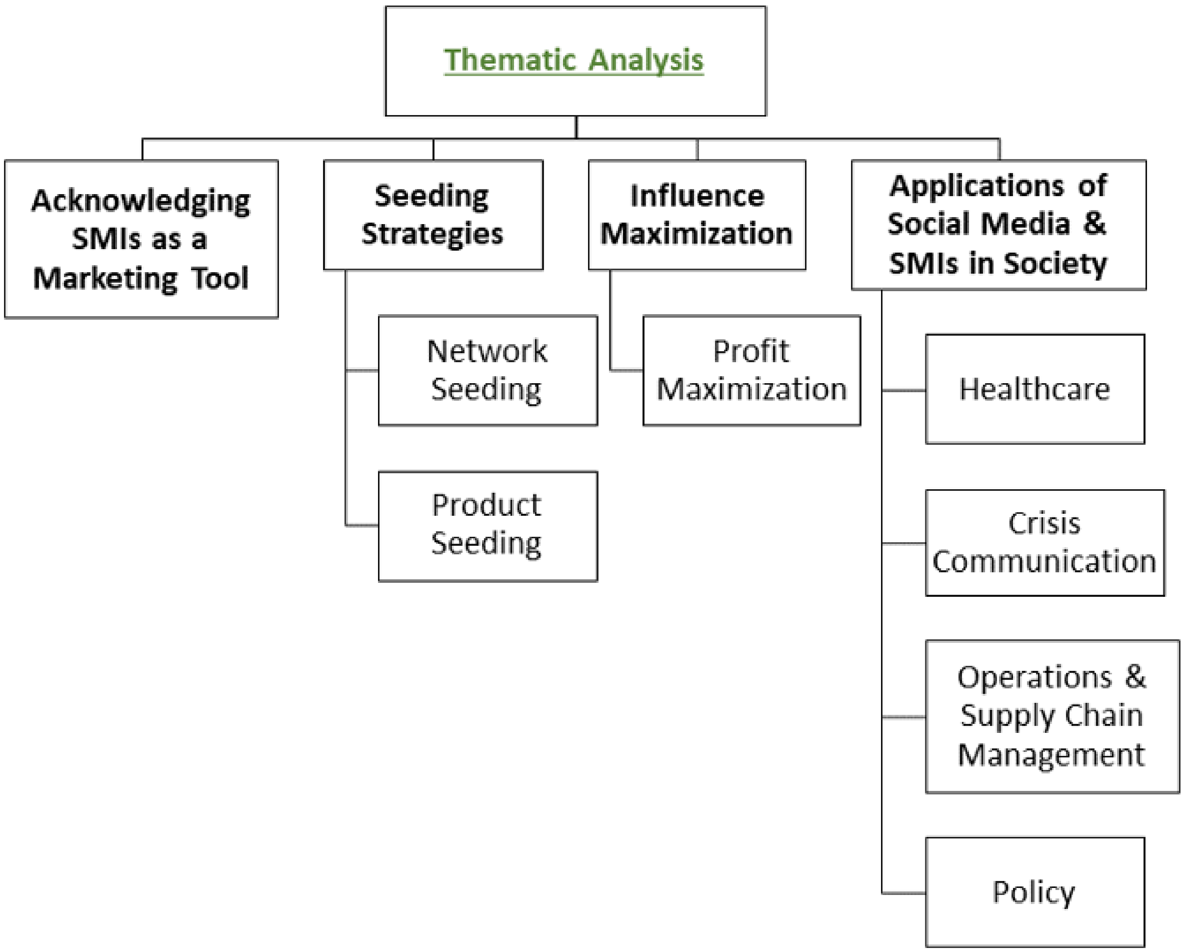

Figure 3.1: Flow of the Thematic Analysis

highlighted by [402] who acknowledged that the Covid-19 pandemic coupled with youth media consumption trends resulted in a proliferation of the already hot topic, which he referred to as "a renaissance". [402] also encouraged academic researchers to investigate whether pandemic trends will have longer-term impacts on influencer marketing. [28] also recognized the importance of SMIs in marketing campaigns and as a result presented an influencer index (scoring method) based on influencer marketing metrics for brands to select the best influencers for marketing campaigns. Additionally, [133] emphasized the significance of investigated the interactions between influencers and their followers and the impact of different types of influencers on new product adoption. Another example of the effectiveness of influencers in brand communication and marketing campaigns was highlighted by [270] who investigated influencers and influencer marketing campaigns in the beauty industry. In their investigation, [270] examined all stages of the influencer marketing process, including the success factors and challenges professionals experience in undertaking influencer campaigns, such as differentiating campaigns, measuring return on investment and managing rewards. Finally, to emphasize the relevance of SMIs in marketing, [296] introduced a five-stage strategy for marketers to follow when engaging online opinion leaders to promote the hedonic (experiential) and utilitarian (functional) value of products and services to consumers.

In addition to the emphasis placed on the proliferation of SMIs and their significance pertaining to brand communication and marketing campaigns, a recurrent theme in the SMI literature is influencer messages and communication styles. An example of exploration into the way influencers communicate is exemplified in the work undertaken by [165] who developed a taxonomy of emojis used to persuade followers and further demonstrated that emojis can be used by SMIs to convince followers. Another example of emphasis being placed on influencer communication is the work of [423] which demonstrated that variations in the features of influencer messages impact their persuasiveness. Also capitalizing on the appeal of influencer communication styles, [138] studied influencer hashtagging behaviour. In this study, influencers were found to use hashtags frequently, primarily due to their desire for self-presentations, to feed their narcissistic tendencies, increase extraversion and promote self-monitoring, more than followers.

Extensive research highlights the factors affecting influencer credibility and the impact of influencers on consumer behaviour [133, 315, 451]. In an examination of the factors affecting influencer credibility and their effect on consumer behaviour, [451] postulated that social influence, trustworthiness, informational involvement as well as social influence significantly impact consumer-perceived information credibility. In their examination, a strong positive correlation between brand/video attitudes and perceived information credibility was revealed. Another example of the exploration of influencer credibility was identified in the work of [133] which investigated the interactions between the influencers and their followers. Their exploration also exhibited the impact of different types of influencers on new product adoption. Finally, [315] delved into the impact of influencers on consumer behaviour and established that consumer behaviour has drastically changed due to the fact that the internet makes mass audiences available to potentially anyone. He referred to this phenomenon as the megaphone effect. These studies provide insights into the reasons why consumers trust influencers and how influencer messages affect their perceptions.

The significance of the relationship between social media and brand value has also been widely acknowledged in various studies [28, 103] . [103] proved the association between social media and brand value by demonstrating that utilizing social media positively impacts brand value. After establishing a connection between social media and brand value, [28] proposed an influencer index to help brands increase their value. An influencer index is a scoring method for influencers based on influencer marketing metrics used by brands to select influencers for marketing campaigns. Altogether, these studies investigated how user actions, influencer marketing metrics, and other social media factors contribute to brand value.

Considering the previously mentioned similarities within the literature on SMIs, let us now shift our focus to the variations that exist. Opinions and perspectives on the same topic within the SMI literature exhibit notable variations. For example, while most studies focus on the positive aspects and large potential of SMIs in brand communication and marketing [28, 103, 133, 165, 270, 423, 451], [352] took a contrasting view by investigating "influencer avoidance" among Gen Z consumers (Generation Z- persons born between 1997 and 2012). The authors revealed that Gen Z's believes the brands' control over influencers to be morally irresponsible. Consequently, this inclination to avoid influencers and endorsed brands results in reduced product adoption [246, 255, 468], particularly when the advertised product is associated with such influencers and brands. This study contributes to the work on the theory of moral responsibility, Gen Z's avoidance behaviour towards influencers and anti-consumption literature. Moreover, it presents insights into how to inhibit acts of consumer retribution towards brands and influencers. The issue of influencer avoidance contradicts the perspective of numerous authors, who argue that Gen Z consumers view influencers as peers and perceive them to be trustworthy and reliable [194, 313].

Furthermore, in the realm of SMI literature, differences in research methods, scope, and data collection can be observed. For example, [165] and [423] used surveys to study SMIs. Specifically, [165] surveyed SMIs by extracting 600 Weibo posts by the top 200 Weibo influencers and [423] conducted a survey with marketing practitioners to gain insights about their future expectations regarding influencer marketing. Additionally, in his study to examine the megaphone effect of social media marketing, [315] surveyed a sample of fashion blogs followed by an analysis of blog texts to analyze the bloggers' tastes and preferences as well as their audiences. This was done to investigate how these tastes and preferences contribute to economic compensation and an increase in social capital for these bloggers. In contrast to surveys, interviews were utilized as an alternative approach to SMI investigation [15, 270]. [270] interviewed marketing professionals in the beauty sector to investigate their perspectives of influencers and influencer marketing campaigns on Instagram. This allowed for a qualitative approach coupled with non-probabilistic convenience sampling. [15] also interviewed industry leaders to form the basis of his predictions for the future of social media marketing (immediate, near and far) as it pertains to the focal stakeholders (consumer, industry and public policy). In his analysis of influencer hashtags, [138] utilized a dual-phase mixed method approach which involved a qualitative analysis of semi-structured interviews with social media influencers and a quantitative analysis of survey data collected from their followers. This formed the premise of a Uses and Gratifications (U&G) study, where uses and gratifications were extracted from the interview data and then summarized into a list of six hashtag usage motives and actual usage. [451] used a heuristic-systematic model to investigate the impact of YouTube influencer informational cues on the consumers' perception of credibility as well as a survey to examine the associated factors. Various models were also formulated to examine SMIs. Subsequent to his data collection exercise, [103] proposed a conceptual model and tested it empirically using partial least squares path modelling (PLS-PM). Instead of using a single data source like [270] and [133] who used Twitter data, [103] collected data from Facebook, Twitter and YouTube for 87 brands in 17 industries. Initially, they found that user actions on YouTube and brand actions on Facebook positively influence brand value. Word-of-mouth (WoM) was then introduced as a mediator which led to the discovery that the effect of social media far exceeds pure WoM diffusion. In combination with qualitative data extracted from Instagram, [133] used machine learning algorithms and social network analysis to determine the individuals with the most influence on the behaviour of the social network. These methodologies, although diverse, offer valuable insights into influencers' persuasive functions, audience reach and effectiveness.

Within the domain of SMI literature, significant differences also prevail in the measuring techniques proposed to determine influencer impact and the methodologies employed to construct them. [451] and [28] presented specific mechanisms and techniques for measuring influencer impact and credibility. In addition to using a heuristic model and survey to study influencer credibility, [451] employed a structural equation modelling methodology in tandem with data analysis to investigate the correlation between variables affecting credibility. To develop an influencer index, [28] used a regression approach in which they modelled features that affect consumers. This work was then complemented with machine learning algorithms to calculate a cumulative score with regard to the influencer index. From this, they were able to determine the variables which play a fundamental role in selecting the influencers. Moreover, [133] evaluated influencers' reach and relative importance among their network peers by proposing the eigenvalue centrality measure, a measure of the influence a node has on a network based on concepts of linear algebra, and the betweenness centrality, a measure of a node's importance in a network based on the shortest paths between pairs of other nodes.

This section has provided a comprehensive synthesis of research on social media influencers (SMIs) and their use in marketing. By analyzing various studies, we have gained valuable insights into the similarities and differences across different areas of SMI marketing research. Our exploration has shed light on the significant role of SMIs in brand communication, influencer marketing, and social media research. In our analysis of the SMI literature, key recurring themes include the focus on SMIs in marketing campaigns, the importance of influence and credibility among SMIs, and the role of brand value and social media in marketing. This is of no surprise as the symbiotic relationship between SMIs and brands, supported by the power of social media, forms a powerful marketing strategy in today's digital age. The focus on SMIs in marketing campaigns stems from their significant reach and influence in the digital landscape. The credibility and influence of SMIs make them effective brand ambassadors for promoting products or services to their engaged audience. Moreover, collaborating with SMIs allows brands to leverage their social media presence and credibility to enhance their own brand value and reach a broader customer base. Our analysis also revealed divergent opinions on the integrity and trustworthiness of SMIs in marketing campaigns, variations in research and data collection methods used to study SMIs, and discrepancies in the proposed measuring techniques to quantify influencer impact. Regarding data collection methods, surveys and interviews with marketing professionals and social media users were the most prevalent. Data was also captured directly from social media platforms like Facebook and Twitter using their Application Programming Interface (API). APIs offer access to a vast amount of real-time and user-generated data, allowing researchers to analyze and track influencer activities and interactions with their audience. However, a major disadvantage is the potential limitation imposed by API restrictions, such as the rate of data retrieval and the scope of accessible information, which may hinder comprehensive analysis and require careful consideration of the data's representativeness. Nevertheless, APIs maintain a reputation of reliability and credibility and we expect continued use of this resource. These findings highlight the multifaceted nature of SMI marketing and underscore the need for further research to address these variations and uncover new insights in this dynamic field.

3.2 Seeding Strategies

In our previous section, we analyzed the significant impact that SMIs in marketing and discussed the similarities and variances in the SMI literature. In this section, we will explore the concept of seeding strategies, which involve a deliberate and targeted distribution of products or messages to specific individuals [17, 19, 40, 41, 87, 167, 213]. The goal of this strategy is to initiate viral dissemination across their respective networks. According to [167], a social media marketing campaign begins when a company sends a marketing message to potential customers. These individuals can then share the message with their social network, leading to a repetitive sharing or viral process [38, 115, 419]. The firm's seeding strategy plays a crucial role in stimulating and guiding this information-sharing and propagation process. In different industries and academic fields, these influential individuals are commonly referred to as seeds, nodes, influencers, opinion leaders, mavens, hubs, or influentials. Moving forward, throughout the literature review, we will use the terms seeds, nodes, and influencers interchangeably.

There are two main types of seeding strategies that utilize influencers to promote products and services, but they differ in their focus and approach. These are network seeding and product seeding. Network seeding refers to approaches used to find the most influential people in a network with the goal of maximizing the spread of information within that network. It is often used to market intangible items like digital products and services where influencers use their social media platforms to speak to their audience about the characteristics of what is being advertised. This causes a ripple effect of information diffusion through their network of followers. Product seeding, however, is usually utilized in the marketing of physical products and is referred to as seeded marketing campaigns (SMCs). This type of seeding involves companies sending product samples to selected influencers and encouraging them to spread word of mouth (WOM) via their social media platforms. [77]. The focus of product seeding is on authentic endorsements and reviews that can influence their followers' purchase decisions. Network seeding is associated with information propagation and product seeding is fundamentally new product adoption via opinion sharing. [73] claimed that the major difference between the two concepts is that information propagation utilizes a simple process where one person is sufficient to pass on information. This is usually modelled using a cascade [17]. Cascades are characterized by collective behaviour within a population, where individuals base their decisions on the actions of others rather than relying on their own information, exhibiting a herd-like behaviour. Product adoption, however, is more complex since it is conditional on additional factors including network externalities and price. Network externalities, also known as network effects, refer to the phenomenon where the value of a product, service, or technology increases as more people use or adopt it. Moreover, multiple connections are usually necessary to enhance the product adoption decisions [17, 19, 21, 231].

3.2.1 Network Seeding

The objective of network seeding is to find the most influential nodes in a network to maximize the spread of information within that network. Inherently, the primary questions that arise in this section of literature are “Who do we need to spread our message as far as possible?” and “How do we recruit them?” There has been a myriad of approaches to answer these research questions and the recommendations for what is the best approach are inconsistent. In this section, we discuss these approaches and unpack the reasons for these contrasts.

[154] used a game theoretic analytical model to investigate the process of strategic information spread in networks. The main objective was to understand how various strategies for influencing the diffusion of information or behaviour can be used by network members. Moreover, they investigated the interactions between the network structure and the incentives of the agents, and how these components influence the result of the diffusion process. Furthermore, they identified the conditions under which some seeding strategies are more effective. Ultimately, [154] proposed a seeding strategy which utilizes individuals with low social status or little influence (low-status seeding). However, this is only applicable when the subject of social interaction focuses on exchanging information and the likelihood of adoption increases as the number of adopters in the immediate vicinity increases.

Using a mathematical optimization model, with linear programming and integer programming techniques, [309] investigated short and long-term influencer marketing campaigns. They then advised on how to select influencers, the frequency of which ads should be posted by these influencers and the scheduling of the ad posts on a social media network. The short-term study was based on the premise of selecting influencers on social media (seeding) and accounted for the following three factors: (1) the influencer’s network size (number of users following the influencer) and the strength of the influence; (2) network overlap (multiple influencers having the same followers) and (3) the multiple exposure effect (a user being exposed to an ad multiple times). The long-term study involved concurrently selecting influencers and scheduling their posts over the entire planning period. Beyond the factors considered in the short-term study, an additional factor referred to as the forgetting effect needs to be accounted for in long-term marketing campaigns [309]. [309] found that selecting influencers based on the number of followers they have is a sub-optimal strategy. Taking it a step further, they demonstrated that just selecting influencers as a strategy to optimize the spread of a marketing message was not enough. Instead, marketers must foresee the scheduling aspect when selecting influencers for their campaign [309]. In fact, this study produced a 41% improvement over others that only considered a seeding strategy without giving any attention to the scheduling of influencers' posts.

Contradictory to the simultaneous seeding and scheduling strategy proposed by [309], a case for adaptive seeding was put forward by [159]. They postulated the reason for this is that the dynamics of influence cascade in the network and produce a stochastic effect. This approach involved selecting seeds in sequence, contingent on the influence propagation capabilities of the previously selected seeds. Similar to [309], [159] also used a mathematical optimization model. However, they formulated the problem of adaptive seeding as a Markov Decision Process (MDP) and used dynamic programming techniques to solve it. []

[372] used a computational optimization approach with integer programming techniques to select influencers for social media marketing. They indicated that the best way to choose these individuals was for a group of decision-makers, inclusive of representatives from the brand, marketing communication agency and the brand's customers, to collaborate. With each decision maker of the group having more or less equal say in the decision-making process, it shed light on the role of even customers being just as important as all other stakeholders. Consequently, [372] encouraged the decision-makers to examine various trade-offs between different objectives and constraints and to make decisions based on their specific needs and predilection.

Using an analytical game-theoretic model and simulations, [167] derived an optimal seeding strategy to maximize information propagation while considering the competition for attention among network members. This work expanded previous work done in the domain of exchange-network theory which addresses competition in networks [57, 105, 311, 458], and showed that it is optimal to recruit individuals with the highest Bonacich centrality. In a network, the Bonacich centrality is a measure used to quantify a node's influence or relative importance, based on its neighbours' centralities. A node with a high centrality is important in its own right and also contributes to the importance of its neighbours in the network. A limitation of using the Bonacich centrality as a measure of effective seeding is that it requires observing the entire network, which is not usually done in marketing campaigns. Therefore, for practicality, [167] propose a truncated version of the Bonacich centrality measure. This seeding strategy was empirically validated by analyzing 34 social media campaigns on two online social networks via simulations. [167] postulated that this competition for attention, usually explicitly addressed in exchange-network theory, significantly affects the efficacy of seeding strategies. They recommended that people with many friends, who in turn have minimal friends should be recruited. This is because highly connected, popular individuals who receive many messages experience more competition for attention and are less likely to respond or forward them [30, 232, 444]. Further, because these individuals generally receive more information [20, 44, 143, 253], competition for attention and, therefore susceptibility, is dependent on network position. Conversely, there will be little competition for the attention of those individuals' friends and they will be more responsive to the content they receive. Building on the network game of [37], [167] identified which seeds can obtain the most reach in both positively and negatively connected networks.

Also using an analytical model and simulations, [280] endorsed this notion of not seeding the most popular individuals in the social network but instead seeding their friends or connections to optimize information propagation. They found that an unpopular content creator whose goal is to increase their follower base, should "climb" and not "jump". It is suggested that these unknown individuals should gradually build status (climb) by directing outbound activities such as private messages, likes, comments, follows and re-posts to low-status individuals instead of targeting high-status individuals (jump). This research analyzed data from a global leader in user-generated content (UGC) in the music industry. It extended previous seeding literature by proposing the idea of risk to propagation dynamics in online communication. Furthermore, [280] demonstrated that these unknown music creators should go beyond just seeding specific status levels. Instead, they should seed a portfolio of individuals while ensuring that they generate the best return on their investment, considering the risks involved.

In their investigation of network seeding strategies, [441] used network analysis and computational simulation to find that most of the time, high-status seeding does not significantly affect information propagation cascades. Furthermore, multiple studies show that high-status seeds are not necessarily influential [22, 410].

Employing computational social network analysis with sociometric measures, [465] studied the seeds' followers and the effects of macro-level propagation using YouTube data. From this study, he concluded that high-status seeding results in more engagement (measured by clicks on videos) compared to random seeding. This conflicts with [442] who advocates for "big seed marketing". In this approach, many people are randomly selected to maximize the spread of marketing messages for social media campaigns. Many other social network studies recommend high-status seeds [203, 213, 231, 418, 465] to optimize a marketing campaign.

Applying mathematical analysis and simulation, [94] went against all previous systematic approaches for seeding and proposed a stochastic strategy featuring one-hop targeting. This is where seeds are randomly selected then they nominate their network neighbours (friends) to maximize information propagation. This exploits an interpretation of the friendship paradox, first proposed by [142] and revisited by [282], where friends of random individuals are believed to have more friends than random individuals. The subject of one-hop targeting, also known as "nomination" or "acquaintance targeting" has received much attention and advocacy [41, 42, 78, 97, 102, 102, 149, 156, 262, 262, 308]. Beyond that, [94] evaluate previous stochastic seeding strategies by contrasting them and analyzing non-parametric estimators adapted from policy valuation and importance sampling.

Using data analysis and causal inference methods, [446] explored the interaction between influencers' indegree and their engagement (likes, follows, comments, views, shares). Indegree describes the size of the audience an influencer can directly reach with their content. This is the number of followers an influencer has. It is publicly visible on their platform. With sponsored content, there is an inverted U- shaped relationship between influencers' follower count and engagement [446]. In fact, the more followers an influencer has, he or she can attain a broader reach. However, there is a trade-off between their relationship with their followers. As such, engagement first increases, tapers off, then decreases as the follower count rises. Further, [446] explored the effects of content customization and brand familiarity with followers and found that when brands allow influencers more flexibility in customizing the marketing message, and when the followers are less familiar with the brand signal that influencers appreciate their relationship with their followers. Therefore, the inverted U-shaped curve flattens.

Applying a combination of lab experiments and field experiments, [213] compared four seeding strategies and found that seeding to well-connected people is the most favourable approach. This is because more popular people know how to take advantage of their greater reach. Not because they have more influence on their peers than do less-popular people [231]. In the lab experiments, [213] manipulated independent variables such as the type of seeds and the diversity of seeds to observe the impact on the virality of a marketing message. In the field experiments, they worked with an online video game company to execute different seeding strategies in a real-world setting. They then observed their impacts on the message spread among the participants.

It is pertinent to establish that high-status seeding and high-indegree seeding are two distinctly different influencer marketing strategies. High-status seeding entails individuals who have a good reputation or high status in their community. As such, they may attract attention and respect from their peers. However, high-indegree seeding pertains to individuals who have many connections or a high degree of connectivity within their network. These individuals are capable of spreading a message via WOM very quickly but may not be seen as credible as a high-status seed. However, accounting for the assumptions and generalizations of authors, we simplify our analysis by referring to both as high-indegree.

A deep dive into the network seeding literature led us to realize that over the years, numerous methods were employed to find the most suitable individuals in a social network to maximize information propagation. Although the number of papers in this domain is limited, researchers have employed a wealth of approaches such as game theory, lab and field experiments, data analysis, social network analysis, regression models, Bayesian modelling, Markov Decision Process (MDP), simulations, integer programming and integer linear programming. Table 3.2.1 on page 19 illustrates the various methodologies employed by researchers who study network seeding in the context of influencers. Among the research methods used in the network seeding literature, game theory, integer programming and integer linear programming emerged as the most prevalent. Simulations played a prominent role in the network seeding research, accounting for a substantial 42% of the examined literature. In the seeding literature, these simulations were frequently complemented by network analysis, Bayesian modelling, mathematical modelling, and game theory. Notably, 25% of the simulations utilized real social media data, while 17% relied on fabricated data. The use of real social media data in simulations offers the advantage of providing a realistic and dynamic representation of influence propagation in seeding strategies, allowing researchers to observe how information spreads through social networks in real-time. However, a potential shortcoming lies in the complexity of modelling real-world social media dynamics, as it requires significant computational resources and may introduce biases or uncertainties in the simulation outcomes, impacting the generalizability of the findings to different contexts. Nevertheless, the use of simulations is widely accepted as an effective complement to popular methodologies used to study network seeding such as game theory which studies interactions and strategic behaviour among social media influencers, brands, and consumers in marketing campaigns. Table 3.2.1 on page 19 highlights the key methods used in network seeding and reveals a complex landscape with varying conclusions regarding which seeding strategy is optimal. It is evident that the effectiveness of seeding strategies involves a delicate interplay of network structure, dynamics, and objectives, highlighting the need for further research to identify the most efficient approaches based on specific contexts and goals in influencer marketing campaigns.

3.2.2 Product Seeding

Numerous studies tackle the identification of key individuals for new product adoption [19, 34, 176, 253]. In this section, we discuss the different methods used to investigate various areas of product seeding. We acknowledge that various factors influence seeding and the diffusion process. These include how different types of consumers are distributed in the network [18, 314, 341, 370]. Moreover, different methods and modelling assumptions

Table 3.1: Key Methods Used in Network Seeding

Method	**Author**	**Conclusion**
Game theory	[154]	low-indegree seeding
Game theory and simulations (using online social media data)	[167]	high-indegree: seed people who have many friends and whose friends have little friends
Integer Linear Programming (ILP)	[309]	high-indegree seeding and scheduling of influencer content simultaneously
Markov Decision Process (MDP) and dynamic programming	[159]	Stochastic adaptive dynamic seeding
Integer programming	[372]	high-indegree seeding
Bayesian model and simulations (using online social media data)	[280]	mostly low-indegree seeding but create an influencer portfolio which balances risk and reward
Network analysis and simulations (real data set)	[441]	high-indegree seeding is not optimal
Mathematical analysis and simulations (dataset studied by [69])	[94]	stochastic one-hop seeding
Computational social network analysis	[465]	high-indegree seeding
Data analysis and causal inference	[446]	high-indegree seeding but only before the point of diminishing returns
Lab experiments and field experiments	[213]	high-indegree seeding

result in different conclusions which leads to questions being posed regarding the efficacy of different seeding strategies [171, 441].

To examine the function of social influence in the diffusion of user-generated content (UGC) on an online social network, [34] utilized a filed experiment in tandem with a statistical model (a variant of the log regression model). In this study, they referred to this UGC as "assets" and the number of adopting users for an asset as the "asset size". Firstly, the authors modelled the rate of asset adoption as a function of various factors including the number of previous adoptions by the individuals' friends, the popularity of the content and the individual's demographic characteristics. Subsequently, they identified two groups of individuals in the network- influencers, who directly persuade their friends to adopt and early adopters who usually adopt without any influence from their friends and may not be influential in subsequent adoptions. Adoption among friends occurred more rapidly compared to sharing among strangers, although the audience (reach) was limited. Therefore, it was concluded that the rate of adoption as a function of the number of neighbours increased more quickly for smaller assets [34].

[253] also used field experiments and a regression model to verify the assumption that network information can help to distinguish influencers and forecast consumers' adoption probabilities, in a social network. Using an individual-level log-log regression model, the authors characterized people's adoption decisions as a binary choice based on three factors. An individual-level log-log regression model is a statistical model that employs a logarithmic transformation of variables to estimate the relationship between independent and dependent variables at the individual level. The first factor is the local network structure formed by previously adopted neighbours (influencers) which they refer to as "network effects". The second factor is the average characteristics of these influencers, introduced as "influencer effects". The third factor called "adopter effects" captures the characteristics of potential adopters (followers). They then empirically tested the model using data from a European social networking site. Furthermore, several robustness checks were conducted to ensure the validity of their results including a sensitivity analysis which examined the effect of different model assumptions and specifications. It was found that having more influencers increases the likelihood of a follower adopting. While holding the number of influencers constant, having a higher total number of friends decreases the adoption likelihood. Further, a set of well-connected individuals has a stronger influence on a potential adopter than an identical number of sparsely connected individuals. These results are parallel to the findings of [167] who concluded that the influential power of an individual is inversely proportional to the size of the social network. Therefore, having many friends weakens the influential power of an influencer. This is why [167] recommended seeding influencers with many friends whose friends have few friends.

[176] investigated the role of hubs (individuals with a significantly large number of social ties) in diffusion and innovation adoption. To do this, they conducted network analysis and simulations on a data set collected from a Korean social networking site, coupled with statistical methods. From this, the authors identified two types of hubs: innovator hubs and follower hubs, each playing a distinct pivotal role in the diffusion and adoption process. They demonstrated that the innovator hubs determine the speed of the network adoption while the follower hubs impact the number of people who ultimately adopt the innovation (market size). Moreover, the adoption of these hubs enables early prediction of the likelihood of success of a new product [176]. The notion of hubs adopting earlier in the diffusion process resembles the concept of "early adopters" which [34] mentioned were people who adopt without external influence from their peers but were not necessarily influential in further adoptions. Partially contrary to the argument of [441] who also used a data-driven simulation and postulated that high-status seeding does not significantly affect information propagation cascades, [176] contended that social hubs adopt earlier than others from being exposed earlier to innovation since they have more social links- not because they are innovative. Also exploring segmentation schemes in diffusion literature was [418] who presented a model with two adopter segments: influentials and imitators. They argued that influentials are associated with affecting segments of imitators while imitators' adoptions do not affect influentials. This dual-segment framework with asymmetric influence is consistent with numerous studies in diffusion and sociology research [179, 285].

Investigating the capability of word-of-mouth (WOM) seeding strategies when there is homophily (similarities between connected people in a network), [19] utilized an analytical model in combination with simulations to argue that seeding is more effective when homophily is accounted for. There have been numerous studies on the topic of homophily [1, 75, 177, 256, 266, 295, 418]. It is common for researchers to assume persuasion-driven peer influence when modelling product adoption diffusion [54, 68]. Some authors estimated natural peer influence via controlled randomized experiments built to separate influence derived from homophily from adoption based on characteristics [21, 22, 73, 74]. [18] used a dynamic propensity score matching method to quantify natural peer influence.

[77] used empirical modelling in combination with statistical methods to investigate spillover effects (negative and positive) at the brand and category levels in word-of-mouth (WOM) seeded marketing campaigns (SMCs). It was acknowledged that consumer (to consumer) WOM influences consumer behaviour in a plethora of ways. These include customer acquisition, retention and sales [275, 279, 292, 380, 386, 387, 411, 422], consumer choice and purchase decisions [26, 51, 92, 172], consumer expectations and attitudes prior to using the product [13, 210], and post-usage opinions [61]. The authors found that product seeding increases discussion about that product among non-seeded consumers.

Moreover, product seeding reduces WOM about different products from the same brand and competitors' products in the same category as the primary product. This implies that marketers can utilize SMCs to concentrate online WOM on a specific product by diverting customers away from other related but off-topic products. Brand spillover effects (when marketing activities for a product impact consumers' attitudes and behaviour towards other products from the same brand as the main product) and category spillover effects (products in the same category but from different brands as the main product) have been examined by numerous authors [12, 36, 136, 161, 290, 293, 374]. However, spillover effects are not discussed in the context of WOM or SMCs as is the case with [77]. It is worth noting that this form of WOM is encouraged by the firm (amplified WOM) and is different from natural (organic) WOM which occurs without any participation from the firm [292].

The product seeding literature encompasses a diverse range of methods aimed at understanding the dynamics of seeding strategies and their impact on product adoption. The exploration of various areas within product seeding has led to a multifaceted understanding of how different factors influence the diffusion process. Table 3.2.2 on page 23 shows a summary of our survey of the product seeding literature. The studies surveyed collectively showcase the importance of network structure, consumer characteristics, and the interplay between influencers and adopters in shaping effective seeding strategies. Field experiments, regression models, network analysis, and simulations were the more widely employed research methods. Empirical and analytical models are also featured, albeit to a lesser extent. The diverse array of research methods utilized in these studies to target different aspects of product seeding highlights the complexity and importance of understanding the intricate dynamics of social media influencer-based seeding strategies. Such insights can serve as valuable resources for marketers and policymakers seeking to optimize the impact of seeding initiatives in social media contexts. By employing a combination of experimental, analytical, and statistical methods, researchers have provided valuable insights that can guide marketers and policymakers in optimizing the impact of seeding initiatives within the realm of social media influencer-based strategies.

Ultimately, the literature on network seeding and product seeding presents a comprehensive exploration of strategies aimed at maximizing information propagation and product adoption within social networks. While network seeding focuses on identifying influential nodes within a network to facilitate the spread of information, product seeding centers on understanding the dynamics of seeding strategies for new product adoption. The congruence in the employment of research methods, namely field experiments, regression models, network analysis, and simulations, within both network seeding and product seeding research underscores the efficacy and robustness of these methodologies within the scholarly domain. The studies conducted within each domain emphasize the significance of network

Table 3.2: Key Methods Used in Various Focus Areas of Product Seeding

Focus	**Method**	**Author**	**Conclusion**
Diffusion of User Generated Content (UGC)	Field experiment and statistical modelling (a variant of log regression model)	[34]	The rate of adoption as a function of the number of neighbours increased more for smaller "assets" .
Adoption decision as a binary choice	Field experiments and regression model (individual-level log-log regression model)	[253]	A set of well-connected people have a stronger influence on potential adopters than the same number of sparsely connected people.
The effectiveness of seeding strategies under various social conditions	Threshold model and data-driven simulations	[19]	1) Considering homophily in seeding strategies increases the effectiveness. 2) The effects of seeding are limited to the number of potential influencers in the network. 3) Seeding is more effective when there is more social influence.
The role of hubs in diffusion and innovation adoption	Network analysis, simulations and statistical methods	[176]	Different types of hubs (innovation hubs and follower hubs) play different roles in the diffusion and adoption process.
How seeded marketing campaigns (SMCs) impact Word of Mouth (WOM) spillover effects (brand and category levels)	Empirical model and statistical methods	[77]	1) Product seeding raises conversations about the product among regular (non-seeded) consumers. 2) Product seeding reduces WOM about products from the same brand and competitors' products in a similar category as the main product.

structure, consumer characteristics, and the interplay between influencers and adopters in achieving successful outcomes. As marketers and policymakers seek to harness the power of social media influencer-based seeding, the insights gained from these research endeavours provide invaluable guidance for optimizing the impact of seeding initiatives in the context of contemporary social media landscapes.

3.3 Influence Maximization

After the influencers have been selected, the next step is to maximize the influence in the network. Social influence maximization involves not just finding the most influential people in a network but identifying the smallest number of seeds to maximize the diffusion of information or behaviours through a network [17] with the least investment. Numerous models of information and influence diffusion have been declared in an assortment of applications. These include outbreak detection [287], cascading behaviour and prediction [91, 286], information spreading [324] and viral marketing [53, 256]. In this paper, we direct our attention to approaches proposed to tackle the influence maximization problem (IMP) within viral marketing. [127] and [361] were the first to introduce viral marketing to the data mining community by using Markov random fields to model the influence among customers and then selecting the most suitable marketing plan to maximize profits.

Influence maximization is a prominent algorithm technique for viral marketing [434]. It is important to indicate the two components of the IMP model that the studies we discuss utilize. Firstly, there is an influence diffusion model which ascertains the diffusion process and the triggering mechanism of word-of-mouth (WOM) marketing. Secondly, there is an algorithm that finds the optimal or sub-optimal seed set under the diffusion model.

[256] first tackled the influence maximization problem (IMP) using network optimization problems. The authors presented a broad class of influence propagation models which included the linear threshold (LT) model and the independent cascade (IC) model. The IC model [177, 178] and the LT model [185] are the two classic progressive models. In IC models, diffusion at every edge in the social network occurs mutually independently while LT models experience stochastic diffusion. In a probabilistic environment, given a budget of seed products, [256] identify a set of individuals to target to maximize node activation in the social network directly. Furthermore, they proved that finding this optimal seed set is NP-hard and developed a (1-1/e) approximation algorithm for the problem.

Since then, IMP has attracted much attention [84, 86, 302, 335, 336, 398, 406]. Improving the precision of measuring the propagation probability of social networks influences costs, labour and time for information diffusion to achieve the best return on investment [464]. Therefore, marketers are generally concerned about this, especially the time constraint and spreading speed of their campaign messages because they affect profit and competition [434]. As such, we seek to shed some light on researchers who tackle this problem.

Notably, [170, 195, 196, 450] also address influence maximization problems in a probabilistic setting from a maximization perspective. [450] proposed a two-stage stochastic programming framework for the IMP. They used the submodularity property in the objective function to propose a delayed constraint-generation algorithm and further performed computational experiments on the stochastic version of the IMP. However, this approach was limited [199] because it was only viable for small seed sets (of size five) while heuristics in the literature used much larger seed sets. For example, [256] studied seed sets with 100 nodes. [197] proposed a branch and cut algorithm [355, 357] under the IC model for the influence maximization problem, by modelling it as a stochastic maximal covering location problem.

[325] presented a dual-phase approach to the influence maximization problem, designed based on a Suspected-Infected (SI) epidemic model. They found that their SI-based algorithm achieved better results for the speed and overall influence spread in comparison to the greedy algorithm [256]. Consequently, they demonstrate that the graphical structure of the social network may be altered to improve the reachability and hence improve the influence spread. Like [325], all authors studying the influence maximization problems sought to improve on the inefficiencies of [256].

[286] found that the performance of the greedy algorithm for influence maximization can be enhanced by developing the property of submodularity, by a technique known as Cost-Effective Lazy Forward (CELF) selection. Subsequently, [184] proposed CELF++ which is an improvised algorithm that exploits the submodularity of the spread function. [265] modelled social network diffusion using multiple theories like bond percolation which lead to the proposal of an extension of [325] called the Susceptible Infected Recovered (SIR) model. Compared to the SIR model, the SI model is progressive and so it can be better utilized in the influence maximization problem. As such, it is deemed superior to the SI model [325].

[80] tackled the influence maximization problem with an approach known as Target Set Selection (TSS) problem, in a deterministic setting with a cost minimization aspect. This is different from a case where the decision maker (firm) has a budget. Instead, the objective is to select the minimum number of individuals in the network to target so that the whole network is influenced. Their influence propagation problem followed an LT model and they

offered a polynomial algorithm for the TSS on trees. Numerous authors proposed a version of the TSS problem with the objective of selecting a seed set of nodes to maximize the number of activated nodes at the end of the influence propagation process [83, 85, 256, 428]. [82] summarize the relevant work done in this domain.

[355] examined the weighted TSS (WTSS) problem. This occurs in a deterministic setting and takes a cost-minimizing perspective. With the WTSS approach, each node has an associated weight to highlight the fact that the decision-maker may incur different costs in attempting to make each node active. [357] postulated that it is noteworthy that previous work did not consider the difference between "direct influence" and "indirect influence". Direct influence is received from a node that has been chosen for targeting while indirect influence is received from a node that was not selected for targeting. Multiple studies demonstrate a substantial increase in the extent of direct influence compared to indirect influence [174, 472]. Specifically, [174] studied the diffusion of close to a billion videos, pictures, news stories and petitions on Twitter to find that over 99% of cascades terminate within one time period. Therefore, they concluded that direct influence was the only type of influence propagation strategy worth exploring. Conversely, numerous studies argue that diffusion models that consider direct influence exclusively are inefficient [140, 434]. Specifically, [140] found that this limits the predictive power of the model and [434] argued that messengers play a crucial role in influence diffusion for viral marketing and accounting for this indirect influence makes the diffusion model more realistic.

As such, [357] focused on direct influence in combination with their assessment of the WTSS problem to land at a generalization of the Positive Influence Dominating Set (PIDS) problem. Initially, the authors presented an extended formulation for the PIDS problem. Then, they projected the extended formulation onto the space of the natural node-selection variables to acquire an equivalent formulation with an exponential number of legitimate inequalities. They implanted the exponential size formulation in a branch and cut structure and lead computational experiments in real-world instances. In the PIDS problem, all influence propagation in the network occurs in a single step or time period. However, in the WTSS problem, the time periods or steps are not limited as it pertains to influencing the entire network. Consequently, the PIDS problem is referred to as the "rapid influence maximization problem" [357, 476]. Notably, the PIDS problem is characterized by a deterministic setting with a cost-minimization aspect.

[430] and [123] proposed greedy constructive methods for the PIDS problem. [429] proposed an iterative and greedy algorithm for the PIDS problem and tested it on a real-world online social network data set. [112] suggested a learning automation-based meta-heuristic algorithm for the PIDS problem. They also examined a budgeted variant of the TSS problem forwarded by [256] and empirically proved that confining the seed nodes

chosen to be a subset of a PIDS produces improved outcomes compared to six existing popular algorithms for the problem.

Expanding the scope of the WTSS problem by accounting for "partial influence" (by providing coupons) to individuals who are not directly targeted, [198] and [199] examine the Least Cost Influence Problem (LCIP) and defined it as NP-hard (similar to [256]). [199] examined the geometry (polytope) of the WTSS on cycles and trees whereas [198] studied a branch and cut approach for arbitrary graphs (representing a social network) and tested it on real-world graph instances. The objective of the LCIP is to reduce the sum of the costs of direct targeting as well as partial payments made to influence the network. This use of coupons to influence purchasing (or product adoption) decisions is a form of intervention which the authors claim is a more practical and cost-efficient approach compared to alternative mechanisms of intervention such as giving seeds free products [329] to accelerate the propagation process. Referral programs are another method of intervention. A popular method used by companies is to offer discounts to customers as compensation for each friend they refer [54, 68, 291, 359, 365]. It should be noted that [190] and [191] described the LCIP prior to this, where it appeared in a product-design setting which accounted for social-network effects.

Although the WTSS problem is similar to the LCIP, there are a few distinguishing factors. Firstly, in the WTSS problem, all neighbours have the same influence. This scenario is relevant especially because privacy concerns exist in social networks. As such, the influence would not depend on the identity of the neighbour and the information available on the strength of the relationship. Notably, equal influence from each neighbour does not mean that each individual has the same factor. Secondly, the intervention or payment strategy is different. In the LCIP, there is partial payment to reduce the cost of the product. However, in the WTSS, the individual is either paid the full amount or nothing at all. Finally, the WTSS is associated with full adoption in the network. This is not the case for the LCIP.

[121] put forward a fractional version of the IMP which was identical to the LCIP, such that nodes can be partially influenced via electronic payment to maximize the number of influenced nodes in the network given a budget. The authors adopted the same technical assumption as [256] regarding the uniform distribution of thresholds and considered the budgeted version of the problem. Theoretically, they proved that the fractional variant of the IMP yields the same computational complexity as the original IMP.

[109] investigated a problem which corresponds to a specialized version of the LCIP in which the influence factor is the same over the entire network and produced a polynomial time algorithm for complete trees and graphs. [148] generalized the LCIP to consider

instances with a nonlinear influence structure (there is diminishing influence or increasing influence from each extra neighbour), when neighbours have unequal influence or when achieving adoption in the entire network is not necessarily the goal. The authors presented a novel set covering-based formulation which had an exponential number of variables as well as an exponential number of constraints. With this formulation, they described a branch-and-cut approach and further outlined a heuristic approach and an exact approach on graphs.

To address influence-diffusion modelling and maximization as it pertains to viral marketing, [434] proposed a novel multiple path asynchronous threshold (MAT) model. Unlike [356] who focused on direct influence only, [434] used his model to capture direct influence from neighbouring influencers along with indirect influence from other messengers to quantify influence and track its aggregation and diffusion. Their MAT approach modelled individual diffusion dynamics, influence depletion along diffusion paths and temporal influence decay. The authors conducted experiments on real-world networks and developed a heuristic to grapple with the influence maximization problem. Moreover, the authors reviewed product adoption as a three-stage process (which they called the 3A process) of influence diffusion. Firstly, "awareness" (an individual is exposed to the WOM message). Secondly, "aggregation" (the individual progressively experiences more WOM exposures). Thirdly, "activation" (the individual adopts the product when the aggregated influence is greater than their threshold). In previous work, [432] and [433] developed a reachability-based influence diffusion model to address the implicit knowledge of influence-based connectivity and vertex-pair similarity ciphered in the network graph topology.

[464] proffered an algorithm that incorporates the Barabasi-Albert model [45], binary-addition tree (BAT) algorithm [463], PageRank algorithm (originally used by Google), personalized PageRank algorithm and a BAT algorithm, on a scale-free network to deduce the propagation probability of social networks. They then executed a simulation experiment of social network models to prove that their approach increases the efficiency of information propagation in social networks with the minimum investment. The authors emphasized that understanding how information propagates through a social network (via the nodes with more propagation influence) is not only useful for designing winning promotion strategies but also for preventing the spread of malicious information. In the case of the latter scenario, if we are able to pinpoint the nodes with a higher probability of diffusion as early as possible, we can impede the dissemination of information quickly and effectively. Unlike other studies which boast of using indegree as a measure of the probability of propagation in social networks [48, 52, 87, 94, 101, 122, 167, 176, 200, 213, 223, 288, 294, 345, 417, 465], [464] urges against it. They claim that this leads to spam links purposefully created by people in order to increase the probability of the page.

[52] examined the impact of prudent influencers (those who perform due diligence by testing products prior to promoting them) and shallow influencers (those who post the marketing message without conducting any due diligence) on customer satisfaction, influencer payoffs and marketer profits. The authors proposed a mathematical model to optimize the selection of influencers to maximize the product adoption rate within a given budget. This model accounted for three main factors: (1) the size of the influencer's audience (referred to as in-degree), (2) the cost of acquiring the influencer and (3) the probability of the influencer's followers adopting the promoted product. A modified model was introduced later to include a constraint that accounts for a scenario where the product may not be suitable for all audiences. This was followed by simulations to test the effectiveness of their proposed model. Subsequently, it was found that shallow influencers improve customer satisfaction, market transparency and marketer profits. However, prudent influencers contribute to customer dissatisfaction and encourage marketers to reduce information efficiency in the market. Furthermore, using a combination of shallow and prudent influencers may lead to higher adoption than employing one type of influencer in a marketing campaign.

There have been several extensions of the class LT and IC models to various scenarios. [83] extended the IC model to account for the emergence and propagation of consumers' negative opinions. Later, [81] modified the IC model to the topic-aware influence propagation, where the influence probability on each link depends on the respective topic distribution. [64] and [209] extended the LT model to tackle the IMP under competition. [164] altered both the IC and LT models to investigate influence diffusion in dynamic networks. Notably, like [256], all of these models are probabilistic models.

[53] modified the LT model to what they referred to as linear threshold with colour (LT-C) model. The authors demonstrated that there exist "tattlers" who may be activated without actually adopting the product and who do not need to be activated to spread influence. As such, they found that tattlers are usually messengers [434] who transmit indirect influence. This aspect of WOM was also described in the network co-production model proposed by [268].

[132] tackled the problem of influence maximization (choosing a set of k seeds with maximum expected diffusion size) when the social network is unknown and network information is expensive to obtain. By observing the influence spread among random nodes (influence sampling) via an experiment and by divulging the identity of neighbouring nodes in an adjacency list (edge queries), they investigated two methods of acquiring network information. Using a bounded number of queries (for the amount of network information collected) to the graph structure, they produced polynomial-time algorithms with almost tight approximation guarantees for approximating the optimal seed set. They also proposed a probing algorithm which queries edges from the graph and used this to obtain a

seed set with a similar almost tight approximation guarantee. These algorithms were tested empirically to quantify the trade-off between the benefit of additional information for leading improved seeding strategies and the cost of obtaining it. Similar to [17, 159, 309, 442], [132], use the independent cascade (IC) model of social contagion which has received much attention since its use by [256]. The authors refer to active nodes as adopters which adoption propagates from and through the network. The process terminates after a finite set of steps.

Particularly relevant to the contribution of [132], is work on influence maximization for unknown graphs [317, 318, 385, 447, 448]. [317] applied a biased snowball sampling strategy to probe and seed nodes with the highest degree. They then offered to enhance their heuristic by including random jumps which avoid too many local searches in their snowball sampling strategy [318]. [385] studied applications of known heuristics and common algorithms in scenarios where sections of the network are unobservable. [447] used a stochastic block model to test the robustness and stability of influence maximization under uncertain cascade probabilities. According to [132], this is the lone existing guarantee for influence maximization with unknown graphs.

Due to marketing managers having limited budgets for marketing campaigns, they usually strategize about where in the network to intervene to maximize the acceptance of the marketing message (seed a behaviour) [42, 127, 173, 213, 256, 294]. This intervention may be in the form of distributing free products in the network with the objective of gaining new product adoption from potential customers.

[238] investigated the optimal intervention decision of a firm (which they refer to as an influence designer) when there is social learning in a network of individuals. The designer attempts to sway agents who already have preconceived opinions to change their opinions to something close to the target opinion. They do this by introducing or "injecting" new private opinions, subject to a budget constraint. By decomposing the influence matrix, which outlines the learning structure, [238] altered the problem into one with an orthogonal basis. This means that injected opinions on one group of agents only influenced one other group's opinions, in a ripple effect. The authors define the optimal intervention of the designer with complete information in the context of authority and hub centrality (measures of the importance of a node based on its position in the network). They also examined the scenario with incomplete information regarding the network structure.

[310] investigate a model where individuals contact their neighbours randomly and independently, and each contact leads to adoption with some fixed probability. Besides the mathematical models and algorithms proposed to solve the influence maximization problem, there are numerous (complementary) behavioural and experimental studies addressing

diffusion in real-world networks. These observational studies typically emphasize influence dynamics including the effect of network structure and influencer location, the identification of influencer characteristics, understanding and peer influence and types of sharing on the final spread [22, 44, 73, 412].

[17] proposed empirically motivated influence models and studied how they affected influence maximization in six synthetic and six real-world social networks of diverse sizes and structures. The authors found that accounting for assortativity and joint distribution of influence and susceptibility yields better results for influence propagation compared to traditional influence models. Moreover, it was postulated the optimal seeds selected via empirical influence models are less well-connected (as measured by their indegree), are less central nodes and hold more cohesive, embedded ties with their neighbours in comparison to seeds chosen by foundational models from the existing influence maximization literature. Therefore, empirical influence models can potentially identify more practical sets of seeds in a social network and advise intervention designs that provide information or change attitudes and behaviours [17]. It is worth noting that, similar to [17], [155] and [419] also employed empirical studies approach with real-world networks or datasets to examine influence maximization.

[155] developed a game theoretic model where players personally acquire information and form connections with others to obtain their information. Their study yielded two main findings which they called "The Law of the Few": (1) In social settings, most people get the majority of their information from a tiny subset of the entire group (the influencers). (2) There are insignificant differences between the demographic and economic characteristics of the influencers and the other members of the group. Their study also gave rise to the insight that indirect information transfer triggers a new type of influencer called the connector. This is someone who connects other individuals so that they can acquire information themselves but he/she acquires little information on their own.

[419] proposed an extended viral branching model (based on the theory of branching processes) to enable customers to participate in a viral marketing campaign in two ways: by (1) opening a seeding email from a firm, (2) opening a viral email from a friend, and (3) responding to other marketing activities including banners and offline advertising. Their model differs from the standard model in a few ways. First, the base branching model is a Markov process with a fixed transition time. However, they permitted customers to participate at any time which resulted in a Markov process with stochastic transition times. Secondly, instead of merely traditional advertising, [419] incorporated seeding via external sources like banners in addition to the traditional approach. Thirdly, branching models usually count the number of customers who receive emails and did not participate yet or deleted the email (infected customers). Conversely, their model counts the aggregate

number of customers who actually participated. Finally, the base model assumes that parameters are constant over time. Instead, the authors accounted for a scenario where new invitations become less effective during the campaign (diminishing returns), since customers who may have already participated in the campaign or received an invitation may continue to receive new invitations. This model was then tested with a real viral marketing campaign organized over a six-week period. The authors argued that this approach helps marketers in two main ways. Firstly it assists in predicting the number of customers a viral marketing campaign will reach. Secondly, it helps them to understand how they can influence the viral process through marketing activities (seeding emails, online advertising and/or offline advertising). In fact, the right strategy for marketing activities at a particular time is influenced by the spread of the process and the effectiveness of the marketing communication tools. Consequently, they urge marketers to carefully monitor the spread of information in these viral marketing campaigns. [419]'s empirical work by starkly contrasts that of [312], [310] and [238] which focused on theoretical models and algorithms.

[312] sought to learn how far a message can travel in a network when sent by different users. Using the Individual Launching Power (ILP) algorithm and conducting computational tests on real-world graphs, the authors proposed a new ILP index for analyzing message propagation in social networks which uses the hurdle coefficient parameter. This work defined the strength of each node as a launcher of the message. Nodes were then separated into launchers and non-launchers. The authors found that launcher individuals can help to choose efficient influencers in a social network, as an alternative to using the node's degree as the primary determining factor. Contrary to other popular studies on influence maximization [80, 148, 199, 355] which consider propagation initiated with a group of individuals, [312] started the message propagation process with one person. Notably, this process of characterizing influence and adoption is deterministic and it exploits an activating condition derived from the LT model.

In summary, in the realm of influence maximization and the study of social media influencers for marketing campaigns, the most effective and commonly used model is the Independent Cascade (IC) model. In contrast, the suspected infected (SI) epidemic model, multiple path asynchronous threshold (MAT) model, and individual launching power (ILP) model are less commonly used in the literature. This is because the IC model allows the spread of influence to occur independently through a network of connected nodes. It provides a probabilistic framework for modelling the diffusion of influence in social networks, making it suitable for understanding how information or behaviour spreads through a network of users, including social media influencers and their impact on marketing campaigns. Other models were found to be useful in studying various aspects of influence maximization in different scenarios, but their applicability and effectiveness depend on the specific

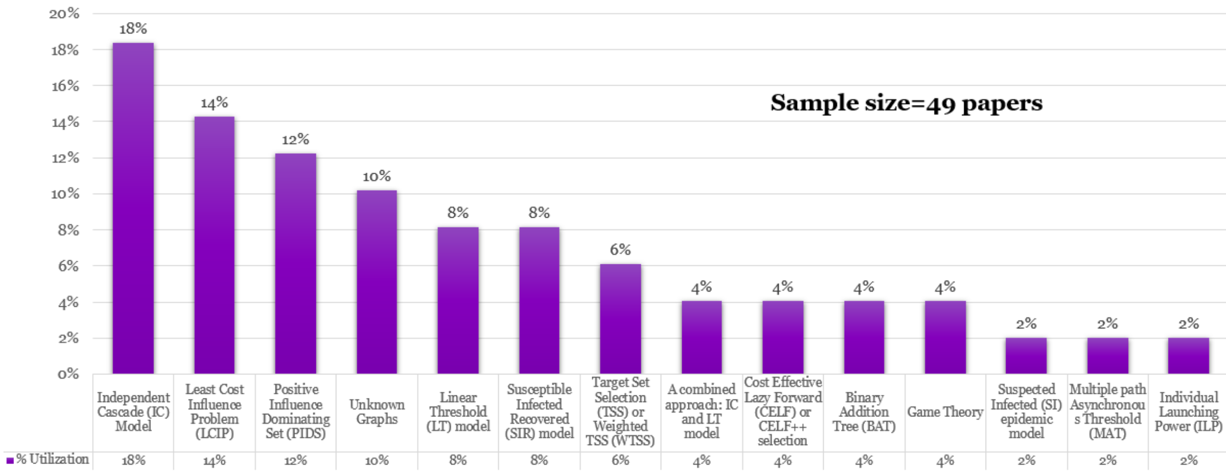

Figure 3.2: The Utilization of Research Methods in Influence Maximization Literature

research context and the characteristics of the social network being analyzed. For example, the Least Cost Influence Problem (LCIP), the second most popular model used in our review of the literature is utilized in scenarios where resources are limited and the objective is to efficiently identify nodes and maximize the spread of marketing messages while minimizing costs. Figure 3.2 on page 33 shows the use of the aforementioned research methods to solve the influence maximization problem. Table 3.3 on page 34 complements figure 3.2 by illustrating which authors employed each of the influence maximization methodologies in the literature. As researchers navigate this dynamic landscape, the choice of model becomes a strategic decision, necessitating a careful alignment with the intricacies of influence propagation, social network dynamics, and the overarching research goals.

3.3.1 Profit Maximization

In the context of social network analysis, influence maximization and profit maximization have different objectives and the models used to solve them reflect such. Influence maximization models seek to identify a subset of the most influential individuals in a network (called seed) so that if targeted with a message or intervention, will maximize the spread of information, behaviours or opinions in the network. These models generally assume that the spread of influence follows a specific diffusion model, such as the linear threshold (LT) model or the independent cascade (IC) model. Conversely, profit maximization models focus on identifying the subset of individuals in a network to maximize a profit or revenue

Table 3.3: Influence Maximization Methodologies and their Use by Various Authors

Method	Author
Independent Cascade (IC) model	[17, 81, 83, 132, 159, 177, 178, 309, 442]
Linear Threshold (LT) model	[53, 64, 185, 209]
A combined approach: IC and LT model	[164, 256]
Suspected Infected (SI) epidemic model	[325]
Susceptible Infected Recovered (SIR) model	[186, 265, 332, 333]
Cost Effective Lazy Forward (CELF) or CELF++ selection	[184, 286]
Target Set Selection (TSS) or Weighted TSS (WTSS)	[80, 85, 355]
Positive Influence Dominating Set (PIDS)	[112, 123, 357, 429, 430, 476]
Least Cost Influence Problem (LCIP)	[109, 121, 148, 190, 191, 198, 199]
Multiple path Asynchronous Threshold (MAT)	[434]
Binary Addition Tree (BAT)	[463, 464]
Individual Launching Power (ILP)	[312]
Unknown Graphs	[317, 318, 385, 447, 448]
Game Theory	[52, 155]

goal. These models associate these individuals to a certain utility or value. So the objective is to select a subset of people that will yield the highest total utility or value. As such, the objective function is influenced by more factors than that of the influence maximization problem. These factors include the seeding cost (cost of targeting the nodes), the revenue gained from targeting certain individuals, or the expected value of the influenced individuals (based on their connections) in the network. This subsection discusses the extant literature on profit maximization, specifically the approaches taken by various authors to solve the profit maximization problem.

In management sciences, product adoption is typically classified into two steps [248]: (1) awareness and (2) actual adoption. [303] argued that although the awareness aspect is modelled in classical propagation models (LT and IC models), adoption is not captured in the classical models. As such, a gap arises between these classical models and that in [248]. Moreover, they postulated that when companies seek to maximize their expected profit in a viral marketing campaign, they should consider monetary factors, since consumers base their purchasing (product adoption) decisions on the price of the item. Despite this, influence maximization algorithms only account for network structure and influence spread. Additionally, the marketing strategies are limited to binary decisions (whether or not a set of nodes should be seeded).

The authors of [303] proposed the Liner Threshold model with user Valuations (LT-V), an extension of the classical LT model, to optimize profit by accounting for the states of being influenced and product adoption. The model incorporated prices and valuations into the decision-making process for users, with adoption occurring if the quoted price was less than their valuation. The authors used an unbudgeted greedy framework to present three algorithms for maximizing profit, tested on three real-world data sets. The model did not exhibit monotonicity, which differs from the expected influence spread function, and thus requires two decisions for marketing strategies: whether or not to seed a person in the network, and what price to quote.

Addressing the (novel) profit maximization problem from a different angle, [188] examined the non-monotone diminishing return (DR) submodular function maximization over integer lattice. In this instance, the authors prove that it is NP-hard and seek to maximize the net profit earned from a marketing campaign, which is the difference between the marketing costs and the influence gained. They then applied a binary search double greedy algorithm to the problem and proved that it has a 1/2 approximate ratio and the time complexity is polynomial. Further, they postulated that their algorithm is the fastest and has the least queries to the objective function.

Since [256] introduced the IM problem, much research has been done in this area to achieve results in numerous ways [85, 158, 189]. Notably, these analyses are founded on the assumption that the profit of the product is determined by the number of influenced individuals [127, 157, 159, 256, 337]. The IM problem and its extensions take on the knapsack or cardinality constraint which constitutes the seeding budget in a marketing campaign. Hence, the solution, which is a set of the most influential seeds, should maximize the influence spread to the other nodes in the network (constrained by the number of seeds selected). The influence spread is a non-decreasing function of the seed sets and so the solution is always an interior solution. In [188], they investigate the overall profit maximization with the objective to achieve the optimal investment to yield the maximum net profit. This takes into account the variable cost of seeding which is proportional to the number of seeds selected. However, unlike the aforementioned studies, in their problem, the objective function is not monotone and the cardinality or knapsack constraint does not exist.

[474] studied the Group Profit Maximization (GPM) problem. Similar to [188], their objective was to select a number of seeds to maximize the expected profit, which is the difference between the revenue from activated groups and the diffusion cost of influence propagation (paid to online social networks). It is important to note that this cost is typically associated with the number of hits on the advertisement. Firstly, they utilized an information diffusion model which was based on the IC model and they proved the GPM to be NP-hard. Notably, the objective function was neither submodular nor supermodular. To achieve a practical approximate solution, they then found a lower bound and upper bound for the objective function that were differences between two submodular functions. The authors subsequently designed a submodular-modular algorithm, motivated by Reverse Sampling Set (RSS) sampling method for solving the difference of submodular functions and proved that it converged to a local point. Moreover, to solve the GPM, they proposed a randomized algorithm based on a weighted group coverage maximization algorithm and implemented a sandwich framework to yield theoretical results which verify the efficacy of their approach.

Solely optimizing the influence spread has proved to be ineffective for maximizing the profit of a marketing campaign [396]. The existing social influence maximization methods cannot be adopted to solve the GPM [474]. This is because the number of seeded individuals selected produces a trade-off between the reward of the campaign and the associated costs. Several researchers have studied profit maximization from the lens of advertisers [303, 475]. These studies accounted for the cost of seed selection which is modular and suggests that their profit metric is still submodular. [397] examined a profit maximization problem that considers the cost of information diffusion over the social network. The profit function was separated into the difference between two submodular functions.

[159] defined the adaptive profit maximization problem (APMP). In this stochastic optimization problem, a seed was selected first, then they observed its influence propagation strength (or lack of it) on other nodes and the resulting profit yielded. Then, the next seed was selected based on the current profits of the influenced nodes, and so on. They proved it to be not adaptive submodular and found upper and lower bounds that are adaptive submodular. Moreover, the authors designed an adaptive sandwich policy contingent on the sandwich strategy. They subsequently tested the effectiveness of the proposed algorithm using real data sets. They studied a scenario where players gamed on a console like Nintendo Switch which allowed for online play mode. In this design, profit represented the revenue associated with the strength of interactions between players and the aim was to select a seed set to maximize profits between activated nodes.

It is worth mentioning that the work of [159] is related to [439]. However, there are a few distinguishing factors. Firstly, [439] studied the activity maximization problem and seek to maximize the sum of activity strength among the influenced nodes by selecting a seed set in one step. However, the optimization problem that [159] addressed was adaptive profit maximization which selects seeds one by one based on current observations, which is different from normal activity maximization. Secondly, [159] proved that their problem is adaptive non-submodular while the problem in [439] is non-submodular.

Instead of considering social influence from the perspective of individuals, [358] focused on high-profit groups. This is a group of people such as the board of directors in a company. The authors claimed that by targeting these individuals, companies can achieve higher profits compared to influencing individuals of the company. This high-profit group typically follows the voting rule like a union. As such, [358] put forward the union-acceptable profit maximization (UAPM) problem select seeds maximize the union-acceptable profit, which is the probability of the union accepting. The authors verified that the problem was NP-hard. Moreover, they demonstrated that the UAPM is neither submodular nor supmodular. To solve the problem, the authors used an estimation algorithm and for the UAPM, a heuristic algorithm and a data-driven approximation algorithm. Subsequently, experiments were conducted using real-world databases. This work was built on the IC model.

In the context of profit maximization, researchers have embarked on a multifaceted exploration to identify optimal strategies for maximizing revenue or profit in various marketing contexts. Differing from influence maximization, profit maximization models consider a range of factors, including seeding costs, revenue from targeted individuals, and expected value of influenced nodes, to craft a subset of individuals in a network that yields the highest total utility. Among the multitude of research methods employed to address these complex problems, the Independent Cascade (IC) model has stood out as a popular and effective choice, offering a probabilistic framework for modelling influence diffusion in social networks. Notably, the Liner Threshold model with user Valuations (LT-V) expands the classical LT model to incorporate prices and valuations, aiding profit optimization through user decisions on adoption based on prices. Conversely, the Group Profit Maximization (GPM) problem introduces a different perspective, maximizing expected profits while accounting for revenue and influence propagation costs. While the IC model remains foundational, novel approaches like the Adaptive Profit Maximization problem (APMP) and the Union-Acceptable Profit Maximization (UAPM) tackle real-world complexities by considering iterative seed selection or high-profit groups. The models and algorithms devised to address the various profit maximization problems were frequently accompanied by experiments and computational simulations employing authentic datasets to evaluate the efficiency and efficacy of the proposed strategies. This empirical orientation underscores the cognizance of researchers toward the pertinence and utility of accessible data resources in studying the intricacies inherent to the profit maximization landscape. It is apparent that the optimization of profit in marketing campaigns involves complex decision-making processes, where factors such as pricing, valuation, and network structure intersect. While the IC model prevails as a cornerstone, the diverse array of models, algorithms and other accompanying methods like field experiments, network analysis, statistical techniques and data-driven simulations showcases the complexity of profit maximization endeavours.

In conclusion, in the domains of influence maximization and profit maximization within the context of social media influencer-based marketing campaigns, the Independent Cascade (IC) model emerges as a widely employed and effective tool. The focus of influence maximization resides in identifying a subset of individuals who wield the most influential potential, thus propelling the desired message through the network. This primarily entails modelling the spread of influence and selecting influential seeds to maximize information reach. In contrast, the pursuit of profit maximization traverses a more intricate landscape. This pursuit mandates the consideration of a multifaceted array of factors, spanning from seeding costs to the anticipated revenue generated by targeted individuals. Moreover, the ultimate objective revolves around forming an optimal subset of network nodes that collectively yield the highest cumulative utility or value. While the IC model serves as a cornerstone shared by both influence maximization and profit maximization endeavours, profit maximization unfolds a more intricate tapestry. Various methodologies, such as the Liner Threshold model with user Valuations (LT-V), Group Profit Maximization (GPM), Adaptive Profit Maximization problem (APMP), and Union-Acceptable Profit Maximization (UAPM), address distinctive facets of profit optimization within marketing campaigns. These models reflect a nuanced approach by accommodating real-world complexities, including pricing dynamics, user valuations, and interaction costs. Throughout these explorations, empirical validation assumes a paramount role. Researchers, cognizant of the value inherent in real-world data, employ experimental methodologies, computational simulations, and network analyses to assess the efficacy of proposed strategies. This empirical orientation underscores the intrinsic interplay between theoretical constructs and practical applicability, bridging the gap between scholarly inquiry and tangible marketing outcomes.

3.4 Applications of Social Media and Influencers in Society

"Nowadays social media is no longer a choice; it is a must for organizations across all sectors" [459]. In this section, we discuss how service providers use social networks to spread information and influence behaviour change in different domains. This has proved to be a prominent goal in the domain of behavioural science and many researchers have explored the topic [229, 281, 305, 340, 443]. Studies on changing individual behaviour typically involve intervention strategies focusing on psychological factors such as situational cues, attitudinal persuasion and peer influence [7, 169, 404, 440]. Other studies use a seeding strategy to influence new behaviour in the network [40, 60, 73, 414]. These include healthcare, policy, government, retail and supply chain. This section is all about how technology, specifically social media and influencers have revolutionized certain operations within our society. Each application will be discussed as a subsection as follows:

3.4.1 Healthcare

Researchers in healthcare have proposed utilizing social media websites to ascertain how information relating to the textual data on the location of outbreaks, symptoms, spread and severity are shared by users. This data has been collected and used to derive pertinent information [95, 166].

[262] acknowledged that utilizing the distributive characteristics of social networks and targeting influential people to spread messages, improves the effectiveness of health interventions and population health. Using an experiment to test the adoption of chlorine water purification methods and multivitamins, the authors evaluated which target methods generate the most diffusion and as a result, maximize behaviour change in the network. They found that targeting the most highly connected (high in-degree) people (based on the number of times an individual is named as a social contact by someone else) provided no added benefit to the interventions since it produced similar results compared to random targeting.

The authors claimed that in-degree targeting is expensive since it involves everyone in the population stating whom they are connected to so that the entire network can be mapped. However, targeting named friends of randomly selected individuals was more effective than random or indegree targeting for multivitamin adoption and health knowledge diffusion. This is representative of the friendship paradox of human social networks [94, 142, 282]. Notably, this method is more cost-effective since it does not require the entire network to be mapped.

[42] investigated the spread of information about immunization camps. The authors identified influencers in a network without collecting network data and then investigated whether spreading information via these people produces better diffusion than random seeding. In randomized controlled trials (RCTs) in an empirical approach, they asked community members how often they hear gossip (information) about others and who they would most often hear it from. They then nominated these "gossip nominees" to start spreading information and found that information diffuses better when they hit at least one gossip. Like [262], it was also found that these nominated individuals are not necessarily in powerful positions, have high status or even have many friends. Instead, they were just central in a network sense. Notably, [416] surveyed 190 empirical studies of different seeding strategies and found that only four explored asking network members.

Instead of enhancing the spread of information, [78] sought to intentionally cause failure in the social network (stop diffusion) by preventing misinformation about drug side effects in an immunization campaign. They demonstrated that selecting neighbours of randomly selected nodes (acquaintance algorithm) [102, 156, 216] is more effective in fragmenting the network than targeting highly established people (role-based approach) like teachers, healthcare workers and government members. Furthermore, they established that the best people to target to maximize diffusion are different from who you would target to terminate a social network [11, 62, 145, 266]. It is important to note that research in computational influence maximization has produced numerous alternative algorithms for choosing seeds in social networks [63, 100, 256, 286].

[457] studied raising HIV awareness among homeless youth by exploring the challenges experienced when transitioning agents of social influence maximization, HEALER [456] and DOSIM [448] from the lab to a real-world setting. These agents recommended the youth (seed nodes) who were then trained to be peer leaders to enhance the information diffusion process. [49] studied the adoption of contraception using data from a longitudinal household survey. They then developed an analytical model using qualitative data and found that social networks influence people's behaviour via social learning [238] by providing information from homophilous network partners rather than applying social influence.

[259] investigated user-generated content (UGC) in the form of doctors' responses to patient recommendations and questions on a Q&A forum of a healthcare portal. The authors found that including doctor's responses has a prominent causal impact on demand-side user perceptions (patient satisfaction) of medical services. Furthermore, they postulated that doctors' specialty, qualifications, experience and transparency (all attributes of a trusted influencer) in providing services, lessen the effect of their Q&A responses on user recommendations.

[183] also analyzed UGC on social media by studying how governments and healthcare organizations handle disease outbreaks. This UGC comprised ground-level data such as people's reactions, calls for help and feedback which can be used to facilitate the immediate mobilization of aid. [183] selected a novel data set of tweets relating to the Covid-19 outbreak and then proposed an analytical econometric model to segment unstructured data into categories (emotional outbursts, irrelevant posts, distress alarms, relief measures) so that policymakers and humanitarian organizations (supply-side stakeholders) could assess the information on time and optimize relief packages and other resources appropriately and proactively. [160] also examined how humanitarian aid organizations use social media to raise funds, mobilize awareness and even pressure governments. [149] studied the usefulness of opinion leaders to improve healthcare professionals' compliance with evidence-based patient outcomes. They subsequently found that local opinion leaders alongside other interventions or alone, effectively promote evidence-based practice. However, the success regarding patient outcomes was uncertain. [14] used machine-learning tools to predict emergency department waiting times. [39] developed a feature-based algorithm to solve problems relating to nursing staff.

The amalgamation of social media data and influencer strategies has engendered a substantive paradigm shift in the healthcare sector's approach to interventions and population health management. A plethora of methodological approaches has been enlisted to effectively harness the potency inherent in social networks and individuals of high influence. The strategic targeting of influential figures within social networks for the propagation of health-centric messages (seeding) as well as the systematic exploration of information diffusion within networks (influence maximization) were prevalent within our comprehensive survey of the healthcare literature. The systematic acquisition and subsequent scrutiny of user-generated content (UGC) prevalent across social media platforms, coupled with the adept application of machine learning methodologies for the extraction, prediction, and resolution of impending health-related phenomena, have also pervasively permeated the research landscape. This attests to the profound significance accorded by researchers to the wealth of data accessible via social media platforms. Additionally discernible within the purview of our comprehensive literature survey, albeit to a lesser extent, were method-

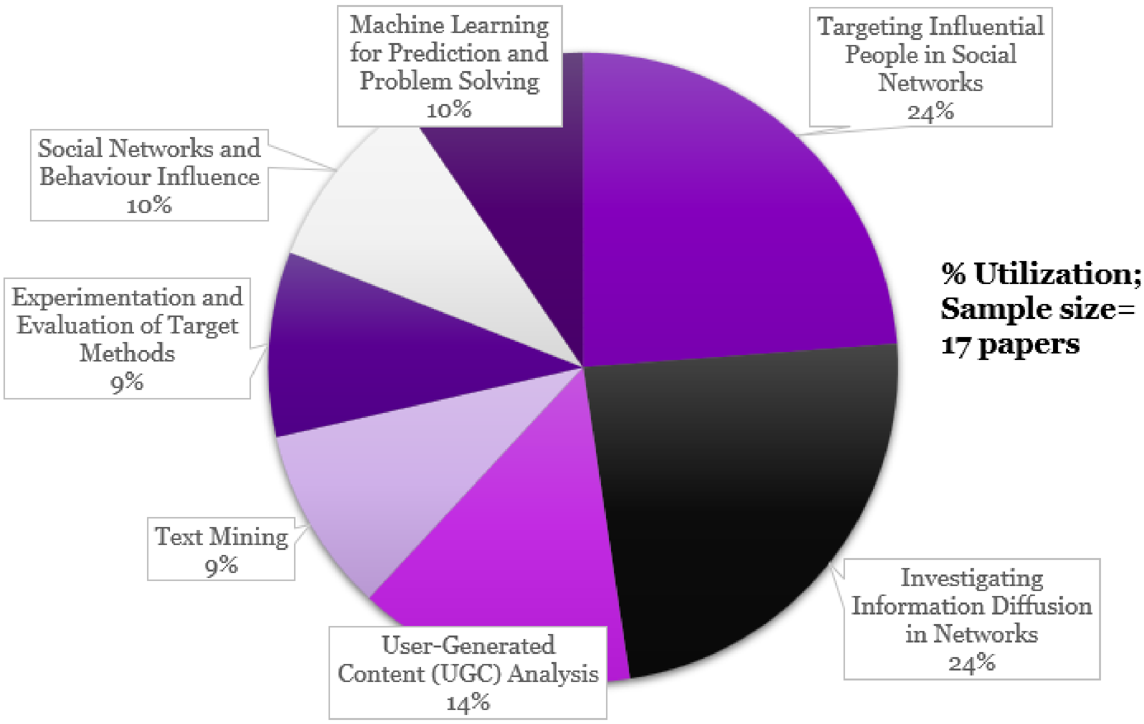

Figure 3.3: The Utilization of Research Methods in Healthcare Research

ological constructs such as text mining, the investigation of social networks and behaviour influence as well as experimentation and evaluation of methods to target influential people. Figure 3.3 on page 42 shows the use of the aforementioned research methods in the exploration of how influencers and social media data are used in the healthcare industry. These diverse research methods highlight the ever-evolving landscape of utilizing social media data and influencer strategies, promising exciting possibilities for improved healthcare outcomes and interventions.

3.4.2 Crisis Communication

[459] postulated that the best feature of social media for organizations is the ability to distribute information to a large population cheaply, quickly and without geographic boundaries. Hence, social media is extremely useful in crisis communication where instantaneous

information dispersion and response is pivotal, often over a wide geographic area and to many people. Studies on crisis communication focus on issues concerning public relations and communication management under varying discrete disasters such as corporate or business environments, food safety, organizational hazards, community, social amplification and government [435]. Crisis communication deals with short-term events [435]. Extant research on risk and crisis communication predominantly focuses on disaster and emergency management during natural or man-made hazards (like earthquakes and hurricanes) [435]. A close examination of the literature relating to crisis communication in hazardous or disaster environments revealed that these studies lie at the border of disaster and emergency management, public health and information science.

Various characteristics of humanitarian crises set it apart from other contexts. Particularly, the negative emotional outbursts laced with anger and pain, the uncertainty of the situation and the urgency to act all contribute to the separation [134, 384]. People have gotten used to sharing content about disease outbreaks on social media as soon as events occur [113]. This includes posting information relating to access to medical assistance, resources and relief packages [134, 459]. Popular media outlets and news agencies even quote and share tweets that they find crucial [309, 459]. Considering that content production is expensive and the fundamental goal of humanitarian organizations (HOs) is to minimize human suffering, HOs will be inclined to maximize their return on investment in content production by enabling its diffusion to the greatest number of stakeholders possible before it becomes obsolete.

Similarly to [88, 466, 467], [435] used the Twitter API to explore the role of Twitter in the dissemination of information and implementation of protective measures during the Covid-19 pandemic. They focused on the communication strategies of government stakeholders and public health agencies in the United States [459]. By analyzing pandemic-related tweets from 67 national and state-level accounts between January and April, the authors employed text-mining techniques and dynamic network analysis to assess the risk and crisis communication on Twitter. They categorized the messages into 16 different types after filtering tweets using Covid-19-related keywords. Communication networks were constructed by examining retweeting and mentioning occurrences, and inconsistencies were identified and analyzed across different topics and agencies. The study also considered spatial disparities, timeliness, and sufficiency of the messages. The dynamic network analysis computed metrics such as network density, average weighted degree, network diameter, average path length, and modularity. The findings indicated an improvement in communication coordination over time. However, it's important to note that the study was observational and didn't draw conclusions regarding the behavioural impacts of Twitter or the types of messages exchanged by Twitter users. This limitation suggests opportunities for future research in this area.

The World Health Organization (WHO) and the U.S federal and state health agencies along with other federal agency stakeholders whose activities involve eradicating the Covid-19 outbreak have consecutively published virus and disease-related content on their Twitter accounts [435]. It was found that Twitter users find it difficult to understand heterogeneous information from multiple sources. As a result of the increasing attention on the use of social networking platforms in extreme events [206, 431, 436, 437, 438, 449, 461, 469], more case studies on social media crisis communication continue to emerge across hazard types such as infectious disease, hurricanes, earthquakes, and other environmental events.

Like [467], the study by [459] explored crisis communication in disaster management, specifically focusing on the impact of information exchange on social media during different stages of Hurricane Sandy in 2012. The author collected data from various organizations involved in disaster response using the Facebook API and Google Trends. To validate their choice of social media platform which is different from [467], [435] [466] and [88] who used the Twitter API, [459] asserted that Facebook was the most popular application in the United States at that time. The analysis involved examining the organizations' posts and users' comments to understand the influence of social conversation, Facebook page characteristics, and user characteristics on the presence of informational support or actionable information in the comments. The study found that the effect of information on social engagement increased from preparedness to response stages but decreased from response to recovery stages. Based on their findings, the author recommended that organizations should utilize social media to target individuals interested in volunteering and donating rather than directing aid information solely toward victims. This study complements other research such as [435], [467] and [328] that primarily focused on providing recovery information to victims while neglecting the areas of donations and volunteerism. It can also complement the work of [134] by including information regarding donation and volunteerism in the coordination and resource-sharing initiatives of humanitarian organizations (HOs). Notably, [459] acknowledged the limitation of not considering multimedia content like videos and photos without text which presents a limitation and future research opportunity.

It is important to note that while the work of [435] focused on one-way communication, which only "pushes" information from relief organizations to the public, [459] was concerned with the social conversations which provide two-way communication between relief organizations and the public. Notably, they focused solely on informational social support in these social conversations which includes operational insights such as the course of the hurricane and evacuation routes as opposed to non-informational social support which involves sending the public uplifting messages. [459] said that there is an emerging stream of literature about how social media platforms facilitate the diffusion of disaster-related information. For example, [467] used Twitter to examine information diffusion during the response to Hurricane Sandy. What primarily differentiates their study from that of [459] is that they studied the dynamics of diffusion without analyzing the content in social conversations. There is also a stream of literature geared towards algorithms used to categorize disaster-related data along with mapping needs and requests. However, there is less focus on using classified data to improve disaster response [459].

[470] presented a study which combined health-related crisis communication with tourism crisis management to identify the main themes and influential words of tourism communication on social media during the Covid-19 pandemic in China. Much like the work of [435] and [459], the authors employed automated text-mining (via the Leximancer software) and manual content analysis to daily comments obtained from TripAdvisor related to coronavirus from January 2020 to February 2020. The content analysis identified the following five (5) topic areas: the impacts on travel, tourist risk perceptions, public health, media coverage and racial discrimination, all of which varied dynamically. According to [470], this is because, unlike natural disaster-induced crises, health-induced tourism crises involve tourist risk perception which in their study was affected by a series of occurrences and concerns as the epidemic developed. The authors argued that the rapid and erratic spread of the coronavirus potentially challenged the classical crisis lifecycle first proposed by [147] which comprises the prodromal (warning stage), acute (trigger event), chronic (lasting effects), and resolution (end of crisis) since a series of updated policies and procedures can exacerbate the health crisis. Furthermore, in comparison to the classical crisis lifecycle, more severe peaks of communication occur when the health crisis is a global phenomenon [470].

[134] investigated a scenario where 23 humanitarian organizations (HOs) can coordinate in the field and share resources. An example of this is the United Nations (UN) investment in the Cluster Approach project (2006-2008) geared towards expanding the overall capacity of relief systems via HO coordination in various sectors of operations such as health, nutrition, logistics, education, sanitation and agriculture [224]. They argued that there is a trade-off between improved cost savings coupled with operational efficiency and reduced media attention for each organization which negatively influences their donation income. The authors empirically tested the effects of media exposure and operational efficiency on their future donation income. Additionally, they used a fixed effects estimation analytical model to characterize the coordination policies as it pertains to an organization's source of funding and mission to reveal the driving forces in humanitarian operations. Furthermore, a Hausman test was run to confirm the choice of the fixed effects model. It was found that media exposure generally has a small impact on institutional donations. Moreover, HOs

whose primary source of funding is institutional donations are more inclined to coordinate with others compared to those whose source of funding is individual donations. Unlike [435], [459] and [470], this work is not confined to a specific disaster event. Instead, [134] studies the impact of media on HO funding from an aggregated annual perspective.

Using a field study centred around Hurricane Sandy, [467] examined the diffusion speed of social media content during emergency conditions. Using a data set derived from the Twitter API, the authors first applied Information Diffusion Theory to characterize the diffusion rates. They then empirically analyzed how different elements affected information propagation rates on social media. This work is similar to [459]'s which also studied crisis communication using a case study of Hurricane Sandy. However, a major difference is the data source used. [459] used the Facebook API while [467] used the Twitter API. A script using the API was run on multiple machines to extract tweets and retweets containing specific keywords. The authors tested this data by comparing it against a sample obtained from Gnip. [467] developed and tested theoretical propositions (using regression) regarding how key factors such as the influence of the cascade originators, the type of content being shared and the timing of the introduction of the information in the network affect the diffusion dynamics in social media networks. The authors found that having larger follower networks of external stakeholders is closely related to rapid diffusion. Moreover, diffusion rates increase when the originator of the message is influential in the network and the earlier information is posted during a disaster, the faster it is spread. It should be pinpointed that this [467]'s integration of information diffusion theory and the fact that the unit of analysis in the study is cascades makes their study closely related to influence maximization which also incorporates the fundamental IC and LT models.

[466] extended this literature by examining the growth of humanitarian organizations' (HOs) follower networks on social media platforms, using a natural experiment based on a major earthquake which occurred in Ecuador in April 2016. A follower network is made up of users who have chosen to connect directly (follow or subscribe) to the HO on social media to receive content released firsthand. The study was focused on the sharing of Twitter content originally produced by 47 Ecuadorean HOs during periods of emergency and normal operations. To tackle this phenomenon, they developed a structural, theoretical, econometric model which assesses the probability of users' decisions to follow a HO after receiving social media content originally produced by the HO through an intermediary (a retweet), as a function of the cost to do so as well as the utility gained. For the utility and cost functions in their model, the authors adopted a Cobb-Douglas functional form [29] and to determine whether someone consumed a tweet, they applied a modified version of [371]'s consumption model. They then estimated the model using the derived Twitter data. The data in this study were sources from two locations. The first data

source was a Twitter subsidiary called Gnip and the second data source was the Twitter API. Text mining techniques were also used to ascertain the type of content in each tweet. Subsequently, the authors found that sharing content and strategically engaging with users to share content yields greater follower networks on social media platforms. Analogous to [459], the tweets in [466]'s work primarily contained informative content.

[50] investigated applications of visual analytics with a focus on sentiment analysis and revealed how sentiment mining in social media can be used to determine crowd reaction during a disaster and how the information extracted can be used to advance disaster management. Sentiment mining is a class of computational natural language processing-based techniques that automatically extracts and condenses the opinions of large amounts of data that the average human is incapable of processing. The authors argued that this method helps to better grasp the dynamics of the network such as users' concerns, panics and general feelings. As such, authorities such as HOs can make faster and better decisions pertaining to disaster assistance while avoiding the costs associated with traditional public surveys. Moreover, sentiment information can be utilized to forecast devastation and recovery scenarios as well as donation requests. The authors acknowledged that datasets have been used from posts on different social media platforms for a plethora of events including hurricanes, floods, earthquakes, gas explosions and terrorist attacks and shed light on how sentiment analysis was used in each example.

[88] evaluated the pros and cons of volunteered geographic information (VGI) for response in emergency management using tweets observed during Hurricane Joaquin in Southern California in 2015. Web GIS was implemented to aid in tweet discovery, geo-tagged tweet mapping as well as management and analysis. They developed a prototype application for dispatching resources by monitoring real-time tweets using two APIs. Firstly, the Twitter API was used to collect tweets with specific keywords, search locations and radii along with other parameters to refine the process. Secondly, for the returned tweets, the Environmental System Research Institute's (ESRI) ArcGIS JavaScript API was employed for mapping. In addition to real-time tweet collection, additional capabilities included live tweet storing in Microsoft's SQL Server geodatabase, live tweet dissemination and real-time geo-tagged tweet operations.

Using framing theory in a case study of the 2010 Haiti earthquake, [328] analyzed Facebook posts and Twitter tweets sent by media organizations and nonprofits to investigate how their social media use motivated and mobilized people during the two weeks after the earthquake. The authors performed a content analysis on the posts and messages from 41 nonprofits and 8 media organizations.

[382] studied the opportunities and challenges associated with using social media for

modelling infectious diseases with an emphasis on their inclusion in compartmental models. Using the Covid-19 pandemic as a case study, the authors argued that despite the significant contribution of mathematical modelling in influencing health policy decisions during the pandemic, social media data are valuable resources to assist in the refinement of these models. It is worth mentioning that [381] was the first to introduce the use of social media in compartmental disease models and [382]'s work is an extension of that. The most common forms of the compartmental models used to model infectious disease epidemics are variations of the susceptible-exposed-infected-removed (SEIR) or susceptible-infected-removed (SIR) models. Notably, these models are used to track information diffusion in the influence maximization literature [186, 265, 332, 333]. [382] found that incorporating social media data into these models allows public health authorities to make better policy decisions, inform the public and organize the necessary arrangements for testing, tracing and treating an influx of cases. However, he argued that, due to the data being in the form of audio, images, video and unstructured text, they are difficult to process using traditional applications and tools. Therefore, data scientists, epidemiologists, modellers and social scientists should collaborate to decipher relationships between phenomena such as public opinion, attitudes and reported behaviour, along with identifying relationships between the extent and severity of the outbreak and patterns of social media activity. This way, the data can be utilized in models with an enhanced understanding of what they mean and how they should be interpreted. We should however bear in mind that although social media data is not bounded by a geographic location, they are limited by the popularity of each platform in the region of study. Moreover, different demographic groups use social media in diverse ways and to varying degrees. Therefore, the data cannot be assumed to be entirely representative of the general population, especially since younger people have traditionally predominantly used social media platforms. With this in mind, we should rethink how we use data from these robust platforms [382].

Contrary to researchers studying crisis communication as it pertains to hazard and disaster management, [376] studied corporate crisis communication. This is where companies partner with social media influencers to strengthen brand image after a corporate crisis. The authors employed a conceptual model validated by two scenario-based experiments where participants were administered online surveys to (1) review a corporate crisis scenario and the consequent response from the company alone, or (2) from the company and the influencer. Applying the theory of persuasion knowledge [153], similarly to [352], they found that consumers perceive influencer involvement as being manipulative, driven by strategic, profit-seeking motives which negatively impact their trust towards the company [193, 452] and in turn worsens corporate reputation [128, 426]. As such, corporate companies should respond to crises by promoting the positive attributes of the company as well as the value-driven motives of the partnership or avoiding influencer involvement entirely. [376] also proved that when companies inform customers that the influencer receives no additional commission for responding to the crisis, the consumer's belief of manipulative intent associated with the influencer's presence reduces. It is worth noting that this work also relates to the Situational Crisis Communication Theory proposed by [106, 107, 108] which outlines four (4) main crisis response strategies, namely, diminish, deny, rebuild and bolster. [376] focused on the bolster response strategy. Specifically, one where a company seeks to minimize the extent of the crisis by employing ingratiation to express its dominance and capitalize on a history of goodwill. The consumer's perception of the brand subsequent to the crisis is examined under the said strategy.

In summary, the exploration of research methods used to study crisis communication, as it pertains to social media data and influencer dynamics, highlights text mining as the predominant approach. The extensive utilization of text mining underscores its efficacy in extracting valuable insights from vast and complex textual data, enabling researchers to discern trends in crisis communication. While text mining offers an unparalleled advantage in its ability to process copious amounts of data efficiently, it does come with certain limitations, such as potential biases, context misinterpretations, and the challenge of maintaining human nuance. Nevertheless, researchers should persist in harnessing text mining due to its capacity to uncover hidden narratives, detect emerging crisis patterns, and provide timely information for decision-making. Furthermore, while text mining holds a central role, other research methods have demonstrated their potential in the study of crisis communication. Econometric modeling, conceptual modeling, sentiment analysis, web GIS, and experiments each contribute distinct advantages to the field, albeit with varying degrees of prevalence. These methodologies offer complementary perspectives that can enhance our understanding of crisis communication dynamics, from quantifying economic impacts to visualizing spatial patterns and gauging public sentiment. By diversifying the toolbox of research methods, scholars can create a comprehensive framework that captures the multifaceted nature of crisis communication, ultimately advancing our ability to navigate and respond effectively to contemporary challenges in an interconnected digital landscape.

3.4.3 Operations and Supply Chain Management

Researchers in supply chain management examine social media data for demand forecasting, better decision making and improved efficiency [222, 375]. [222] explored the value of social media in operations and supply chain management (OSCM) in a systematic literature review. The authors examined the research distribution of various OSCM activities including operations and supply chain risk management, product development and production, marketing, delivery, sourcing, demand forecasting and inventory management and finally, product return and return logistics. With the use of the connecting tool mechanism and the data source mechanism, they showed how social media can improve operations and supply chain activities. It was evident how extensive the topic of OSCM is. Moreover, their work provided some direction for future research. It was found that operations and supply chain risk management along with product development and production captured the interest of the research community. However, product return and reverse logistics (product returns communication and return rate forecasting) as well as sourcing (supplier relationships and supplier selection) attracted the least interest, hence, regarded as primary future research directions. The most popular industry sectors were manufacturing, retail trade and healthcare/social assistance. Conversely, research on social media applications in industries such as warehousing, transportation, finance and insurance is much less. professional, scientific and technical services, wholesale trade as well as administrative support and waste management and remediation services. sector distribution of sampled papers.

[375] studied supply chain management issues in the food industry. The authors used big-data analytics to gather social media data from Twitter (via the Twitter streaming application programming (API) interface) over a three-week period to study the beef supply chain. The proposed method included text mining using a support vector machine (SVM) and hierarchical clustering of tweets with multiscale bootstrap resampling. Subsequently, the root causes of customer dissatisfaction were found and linked to specific parts of the supply chain to improve efficiency. This led to recommendations for a consumer-centric supply chain (a supply chain analogous to the requirements of end customers).

It is a common belief that the food supply chain is more complex than conventional supply chains (like manufacturing) due to the fact that food products are perishable [204, 277]. As such, in an effort to make their supply chains consumer-centric, food retailers consider a plethora of methods including market research, interviews and providing opportunities to customers for feedback in the retail store [375] to improve the organizational, strategic, process-oriented, technology and metrics factors of the company. Supporting the claims of [183] who demonstrated the benefits of social media associated with healthcare, about social media data being qualitative and unstructured in nature, [375] also acknowledged that businesses can use social media to collect real-time data (in the form of customer reactions) to improve the efficiency and effectiveness of current strategies.

[111] used an empirical study to improve the operational decisions of an online apparel retailer. The authors found that using publicly available social media data results in statistically significant improvements in the accuracy of daily sales forecasts. They also

revealed that nonlinear boosting models with feature selection outperform traditional linear models. [111] acknowledged that it is difficult for researchers to process the firm's internal operational data and the external social media data from social media platforms. As such, this may prevent them from examining the operational value of social media data. To overcome this challenge, the authors developed a machine-learning model to capture and process the data. The literature on forecasting is extensive [46, 163, 257, 269, 339, 342, 349].

[354] used a game theoretical model to study how a monopolistic firm can induce behavioural observational learning in social networks by using pricing strategies to maximize its profit. Specifically, the authors formulated a two-period model and compared the optimal pricing policy under behavioural observational learning with that under rational observational learning. They also performed a lab experiment and empirically prove that a seller can control the information available to customers by revealing information incrementally (information-revealing pricing strategy). This induces behavioural observational learning which increases future customers' eagerness to purchase (because they see others purchasing). This result goes against the seeding literature [129, 215] which advocates for introductory discounts given to customers. [354] found that this strategy is not a consistently effective mechanism to boost purchases because it may prevent observational learning. Moreover, consumers are more likely to use observational learning than talk to their friends directly about a purchase decision when the price of the item is low.

Although observational learning has been explored previously [2, 43], [354] postulated that a seller's perspective was not considered in the model. [2] examined an observational learning model over a general social network. [43] built a model where individuals are previewed to all of the choices made by those before them, including anonymous consumers. [354] argued that this is an inappropriate assumption in social networks and extended the literature on the interaction between pricing strategies and observational learning by suggesting a behavioural inference rule which relaxes this assumption made by [43]. It may not be obvious that the work on behavioural learning relates to influencers. However, we believe that the people who share their purchasing history online act as influencers since they have the ability to sway the purchasing decisions of those after them.

[239] proposed an analytical (system dynamics) pricing model based on a live-streaming e-commerce supply chain, with influencers as retailers to examine the impacts of consumers' impulsive purchasing behaviour on manufacturers, retailers and supply chains as a whole. They examined consumers' purchasing behaviour after they witnessed online influencers promote a product via live streaming. They also applied numerical analyses to test the model. Compared to traditional influencer marketing, live streaming permits real-time dynamic interactions which stimulate consumers' desires to engage, thus, causing impulse consumption. [239] found that impulsive consumption benefits manufacturers and influ-

encers equally. Moreover, it boosts supply chain sales and creates increased profits. The online influencer market supply chain comprises brands which act as manufacturers, influencers that act as retailers and live broadcast platforms. Influencers select products, estimate sales, purchase, prepare inventory, sell, and deliver, producing a complete supply chain link [239]. Online influencers are also considered to be small platforms [139] in which they connect marketers and followers via product recommendations. The dynamic is one where marketers compensate influencers to promote their products, in hopes of increasing demand. Followers then read influencer product recommendations which affect their purchase decisions.

Live streaming services have become a popular and widely successful business model [89]. Conducting interviews with employees of a leading live-streaming entertainment service provider in China, the authors explored the phenomenon to deduce the reasons for its success. They found that the Chinese live-streaming broadcast industry, unlike Western social media platforms like Amazon Twitch and Facebook Live which depend on advertising revenue, built its business model on viewers purchasing virtual gifts. Numerous researchers have explored influencer marketing in light of live-streaming sales as it pertains to consumer behaviour [168, 242, 250, 260, 344, 351, 394, 454]. Among the plethora of reasons that may deter consumers from purchasing products on live streaming platforms, [352] found that there is avoidance behaviour towards influencers which leads to anti-consumption among Gen Zs.

Ultimately, our exploration of research methods employed in the realm of operations and supply chain management, with a focus on social media data and influencer dynamics, revealed a diverse landscape comprising six distinct methodologies. These encompass text mining, game theoretic modelling, machine learning modelling, analytical pricing modelling, a systematic literature review, and the integration of interviews with exploratory research. Each research methodology brings its own set of advantages and drawbacks to the forefront. Text mining offers the advantage of efficiently processing large volumes of textual data, revealing valuable insights into trends and patterns. However, it can sometimes overlook nuanced contexts and subtle relationships within the data. Game theoretic models introduce a strategic dimension to decision-making, yet their application might be constrained by the assumptions inherent in the model. Machine learning models empower predictive capabilities, yet their performance relies heavily on the quality and quantity of the training data. Analytical pricing models provide quantitative precision, but they might oversimplify real-world complexities. Systematic literature reviews offer a comprehensive overview of existing knowledge, but they could potentially miss emerging trends or specific contextual nuances. Interviews coupled with exploratory research enable a deep understanding of qualitative perspectives, though findings may be subjective and not necessarily generalizable. While no single method emerged as a dominant choice within the limited sample of papers, the even distribution of various research methodologies demonstrates the need for a multifaceted approach to comprehensively investigate operations and supply chain management in the context of social media data and influencers. Researchers must weigh the merits and limitations of each methodology carefully, tailoring their choice to the specific objectives of their study and the intricacies of the operational and supply chain landscape they seek to unravel.

3.4.4 Policy

The rapid growth in influencer marketing caught the attention of regulatory authorities and consumer protection organizations [139]. On the heels of this, transparency-oriented interventions in Europe such as AGM (Italy's state competition authority) and Landesmedienanstalten (Germany's state media authority) in 2017 and the US Federal Trade Commission (FTC) in 2016 require influencers to explicitly indicate market-sponsored content. It has been shown that the disclosure of sponsorship agreements surrounding SMI's online activities triggers followers' persuasion knowledge which amplifies negative word of mouth [225]. These negative effects seem to decline when the value or characteristics of the products promoted are easy to verify [301] and the followers believe that they are in a beneficial relationship with the SMI [225]. This subsection of the literature discusses studies on the policies surrounding sponsorship disclosure.

[320] developed a dynamic contracting problem model (game theory) without money to investigate the dynamic relationship (continuous interaction) between an influencer and a follower, with regard to revenue. He found that the advice given by influencers on social media sometimes contains company/brand endorsements that are unobservable to followers which elicits a compromise between giving the best advice and gaining the highest revenue in a "reap and sow" cycle. Further, he posited that his model can inform policies such as the FTC mandatory disclosure rules and recommended an opt-in policy which deregulates influencers who are reaping the rewards of past good advice and give followers high returns. Influencers in the sowing phase could publicly opt-in (or else not be followed), whereas in the reaping phase with a reliable history can opt-out and benefit from their advertising mechanisms. It is worth mentioning that policy guidance in this model is dissimilar to a standard model where advice is directly compensated for. In this case, advice is also motivated by the possibility of future attention from followers. [320] emphasized that the main difference between typical media advertisements or paid endorsements and influencer-endorsed advice is transparency. Specifically, the FTC regulations suggest that all sponsorship should be disclosed but this is not always the case.

Similar to the work of [320], [139] used a game theoretic approach to model influencers' trade-off scenario as it pertains to generating more revenue from paid endorsements and a reduction in follower engagement which affects the price influencers receive from brand marketers. This was expressed as a static influencer-follower relationship where followers know when content is sponsored or unsponsored (complete information). Their objective was to yield equilibrium predictions for relative amounts of sponsorship for influencers who are different based on exogenous characteristics labelled as "celebrity status". Moreover, they demonstrated that policies which endorse the transparency of paid endorsement can fail. However, efficient search technology that matches followers to influencers holds positive welfare effects.

Using a game theoretic model, [347] examined the regulatory environment in which the content influencers (bloggers) produce is transparent to followers. An important attribute of this paper was the misalignment of the bloggers' and the firm's incentives. Specifically, bloggers are indifferent between the type of recommendation they make (favourable or unfavourable) and more concerned about whether their judgment of the product is correct. However, the blogger's recommendation affects the firm's sales. The authors demonstrated that in some cases, it is not profitable for a firm to have a blogger exclusively promote their product. Instead, the firm can remove the misalignment by sufficiently paying the influencer so that they are willing to stop signalling.

In the investigation of research methods applied to the study of policy in the context of social media influencers, game theory models emerged as the prominent tool. While game theory provides invaluable insights into the multifaceted world of influencer-policy interactions, it also relies on simplified assumptions that might not capture the full complexity of real-world scenarios. As researchers continue to explore this domain, a combination of game theory, empirical data, and qualitative insights may offer a more holistic understanding of policy implications. This confluence of methodologies underscores the significance of a multi-dimensional approach to comprehending and shaping the evolving landscape of policies surrounding social media influencers.

In conclusion, this comprehensive literature review has provided insights into the diverse research methods employed to explore the utilization of influencers and social media data in various societal applications. Across healthcare, crisis communication, operations and supply chain management, and policy, different research methods have been observed, with some commonalities across different fields. Notably, text mining has emerged as a prevalent and versatile research methodology, utilized in healthcare to target influential individuals for health-related messaging, in crisis communication to assess risk and communication strategies during events, as well as in operations and supply chain management to identify root causes of customer dissatisfaction and enhance supply chain efficiency. Additionally, experimentation has been a widely employed research method across these fields. Machine learning has also gained prominence, aiding in the processing of social media data and improving the accuracy of forecasts in healthcare and operations and supply chain research. Moreover, game theory has played a pivotal role in policy studies, informing policies and regulations pertaining to sponsorship disclosure and influencer marketing. The data-driven methodologies of text mining and machine learning leverage social media data collected through application programming interfaces (APIs), enabling the extraction of valuable insights from ordinary users' interactions on platforms such as Facebook and Twitter. This approach proves advantageous, particularly due to its ability to provide real-time monitoring and data capture capabilities. However, it raises ethical concerns regarding the privacy of social media users. Additionally, the presence of fake followers and malicious online activities may introduce uncertainties about the accuracy and reliability of the information accessed by various industries that heavily rely on such data. Nevertheless, with ongoing advancements in technological mechanisms to detect scams and malicious intent on social media platforms, coupled with the enforcement of data privacy regulations, the continued utilization of text mining for data acquisition across diverse industries remains highly anticipated. As society continues to evolve, these research methods will remain crucial tools for understanding and harnessing the power of influencers and social media data to address diverse challenges and opportunities in various domains.

Chapter 4

Conclusion and Future Research

Our thematic analysis provided a comprehensive overview of the existing literature on SMIs. By highlighting the various research methods employed by scholars, we shed light on the multifaceted aspects of this field. We explored topics such as recruitment strategies, maximizing the reach of marketing messages while minimizing costs, and the application of SMIs and social media in diverse industries including healthcare, crisis communication, and policy. By delving into these areas, we uncovered the transformative impact of SMIs and social media on the contemporary business landscape. In this chapter, we outline underdeveloped and emerging research areas in SMI marketing and make suggestions for future research in the context of our overview of the existing literature.

The intended audience of this paper consists of academic researchers and practitioners including marketers in the private and public sectors. Researchers can deepen their understanding of previous studies to identify the most effective methods for selecting influencers and maximizing information dissemination. This includes examining the approaches employed in proposing seeding strategies and addressing the influence maximization problem. Marketers can enhance their insights by examining the practical work that has been conducted, validating the strategies implemented within their organizations. This allows them to optimize their marketing investments and achieve maximum returns. Public sector representatives can familiarize themselves with the diverse applications of influencers in their industries. By learning from the mistakes and successes of others, they can implement best practices within their own firms and cultivate their own success stories.

4.1 Acknowledging SMIs as a Marketing Tool

Academic research in social media influencers presents a rich landscape for exploration and offers opportunities to advance marketing strategies, enhance consumer experiences, and shape ethical and responsible practices in this evolving field. Given the discrepancies in proposed measuring techniques for quantifying influencer impact, there is a need for standardized metrics and evaluation frameworks. Developing reliable and valid metrics will enable marketers to assess the effectiveness of influencer campaigns accurately. As the use of SMIs in marketing grows, ethical considerations, such as transparency, disclosure of sponsorships, and data privacy, become more critical. Research can delve into the ethical implications of influencer marketing and develop guidelines for responsible practices. Additionally, with the constant emergence of new social media platforms, understanding how SMIs adapt to these platforms and how brands can leverage their influence effectively on these platforms is an area worth exploring. Moreover, considering the varying perspectives regarding credibility and trustworthiness by different groups of social media users, exploring the effectiveness of influencer marketing across different cultures and regions can shed light on the nuances and challenges of running global campaigns. Understanding cultural differences in audience preferences and receptivity to influencer content is crucial for successful international marketing efforts.

There is a vast amount of SMI literature focused on enabling marketing managers to formulate marketing strategies to allow brands to maximize their revenue and/or profit. However, there is a lack of literature centred around revenue and/or profit maximization for platform (e.g., Facebook, Instagram, TikTok, etc.) managers. Though it is happening in practice [421], it remains unexplored in the literature the interplay between influencer characteristics that maximize platform revenue while accounting for external factors such as follower and influencer loyalty/stickiness and exclusivity contracts. Accurate monitoring of influencer metrics is increasingly prevalent in practice as it enables marketing managers to make more precise estimations of reach and, consequently, evaluate their potential returns more effectively. Therefore, we encourage academic researchers to explore this area. Utilizing the prevalent approach of investigating social media influencers (SMIs) through game theory, the analysis can be framed as a profit-maximization problem employing game-theoretic modelling within a principal-agent framework. In this context, the platform manager assumes the role of the principal, and the influencers act as agents in the strategic decision-making process. The objective of the platform manager would be to minimize the costs required to obtain each new influencer and maximize the revenue potential of each influencer under the condition that the influencer is also maximizing their payoffs (pay per post) and agrees to stay on the platform. Conducting research in this area is imperative as it enables platform managers to optimize their revenue model, striking a balance between minimizing costs linked to acquiring new influencers and maximizing revenue potential. Such studies are crucial for informing platform managers about effective strategies for sustaining profitability and ensuring the long-term success of their platforms.

Another topic that is not extensively examined in the SMI literature is the trade-off between sponsored and organic posts. The more sponsored posts (paid advertisement by brands) influencers make on their accounts, the less engagement (likes, comments, saves, shares) they receive from followers compared to when they post organic (authentic) content. However, as much as posting more organic content increases engagement, it lowers the revenue potential for the influencer because brands pay less when there is not enough marketing experience displayed (measured by the number of sponsored posts). [139] modelled the trade-off for influencers between increased revenue generated from paid endorsements with the negative effects derived on the followers' engagement and, as a result, on the price per post influencers receive from marketers. However, there is yet to be a benchmark posting ratio for sponsored content and organic content for influencers to maximize their revenue generation from paid marketing content and engagement. We also believe that SMIs are in constant competition with the platforms they share content on because a company can choose to run paid ads on the platform for a marketing campaign without recruiting any influencers. We are keen on understanding the implications of this scenario for the influencer and the platform. By delving into these uncharted territories, researchers can provide valuable insights and establish benchmarks to help influencers optimize their revenue generation from paid marketing content while maintaining engagement levels.

We also posit that it would be useful to know insights such as which social media platform influencers typically start their career and which platforms they join after. Do followers follow influencers across all platforms? When influencers switch platforms (for example from Twitch to YouTube), do these followers switch as well to follow them there exclusively or do they find another influencer to follow on the first platform? Conducting research on these questions would provide valuable insights into the dynamics of influencer following across different social media platforms, allowing marketers and industry professionals to better understand the behaviour of followers and make informed decisions regarding influencer selection and platform strategies.

With the proliferation of social media influencer careers, it may also be of interest to academic researchers to examine which social media platforms or combination of social media platforms maximize revenue for influencers. For example, given an influencer with a certain set of attributes (number of followers, category and other demographic factors), which platform(s) would be more profitable for them, considering the different pay rates per post, engagement (from users) percentages and brand deal potential? Where do followers start their online relationship with an influencer? How has this changed over the years given the proliferation of new social media platforms and the varying value propositions derived including the potential for exclusive contract generation? Furthermore, which platforms are companies paying the most for brand sponsorship deals? Besides engagement and number of followers, what additional factors contribute to the valuation of companies when offering influencer contracts? Conducting research in these areas will be valuable for academic researchers as it would provide insights into the revenue-maximizing potential of different social media platforms for influencers, offer guidance to influencers in selecting the most profitable platforms based on their attributes, contribute to understanding the overall economic aspects of the influencer marketing industry.

4.2 Seeding Strategies

Future research in seeding social media influencers could focus on addressing the limitations and challenges associated with the use of simulations in studying influence maximization. Researchers could work towards enhancing the accuracy and realism of simulation models by incorporating more complex and realistic representations of social media dynamics, as well as exploring the integration of real-time data streams from social platforms to capture dynamic changes in user behaviour. Additionally, investigating the potential biases and uncertainties introduced by simulations and finding ways to mitigate these issues would contribute to the robustness of findings and improve the generalizability of results to different scenarios.

Furthermore, future studies could delve deeper into the role of influencer credibility and brand value in seeding strategies. Understanding the factors that influence consumer perception of influencers' credibility and brand value can help marketers identify the most effective influencers for specific campaigns and build long-term, authentic relationships with influencers. Additionally, exploring how influencer credibility and brand value interact with different types of products and target audiences would provide valuable insights for tailoring seeding approaches to different market segments.

In the context of product seeding, more research could be conducted to explore the effectiveness of different seeding techniques across various product categories and industries. Investigating how factors such as product characteristics, target audience demographics, and platform features influence the success of product seeding initiatives can inform marketers' decision-making processes and help optimize resource allocation in seeding campaigns.

All in all, future research in seeding social media influencers should strive to combine diverse research methods, leveraging the strengths of each approach to gain a comprehensive understanding of influence maximization strategies. By addressing the limitations of current methodologies and exploring new avenues for studying seeding dynamics, academia can provide valuable insights that contribute to the advancement of effective and ethical influencer marketing practices in the ever-evolving landscape of social media.

4.3 Influence Maximization

Future research directions in influence maximization could focus on exploring the applicability and effectiveness of less commonly used models, such as the suspected infected epidemic model, multiple path asynchronous threshold models, and individual launching power model, in specific research contexts. Understanding the strengths and limitations of these alternative models can provide valuable insights into their suitability for different scenarios and social network structures. Additionally, investigating the integration of multiple models or hybrid approaches to address the complexities of influence maximization in real-world settings could contribute to more accurate and comprehensive results.

Furthermore, researchers could delve deeper into the dynamic nature of influence propagation in social networks, particularly in the context of social media influencers and marketing campaigns. Studies could explore the temporal aspects of influence, considering how influence evolves over time and how influencers' impact may vary based on the timing of their content dissemination. This could lead to the development of time-sensitive strategies for maximizing influence and optimizing marketing efforts.

In the pursuit of profit maximization, researchers could explore the interplay between influence and revenue generation in social networks. Investigating how different influence strategies impact the bottom line of businesses and understanding the relationship between influence and consumer purchasing behavior could inform marketing decisions and resource allocation.

Additionally, as social media platforms and algorithms evolve, future research could focus on understanding how these changes affect influence maximization strategies. Exploring the impact of platform features, content algorithms, and user engagement patterns on the spread of influence can help marketers adapt their approaches to leverage the latest trends in social media marketing effectively.

Overall, advancing academic research in influence maximization would require interdisciplinary collaboration, incorporating insights from network science, data analytics, marketing, and behavioural psychology. Integrating various research methodologies and approaches will lead to a more comprehensive understanding of influence dynamics in social networks and enable the development of more effective strategies for maximizing influence and profit in marketing campaigns.

4.4 Can Seeding Strategies and Influence Maximization Tactics be Optimized Further?

We observed that influence maximization and seeding strategies are usually presented as two isolated marketing approaches in academic research. Influence maximization models typically include the classical independent cascade (IC) and linear threshold (LT) model along with variations of either model. However, seeding strategies often employ game theory, integer linear programming (ILP) or network analysis. The influence maximization algorithms help identify influential nodes or individuals in the network, while the seeding strategies and optimization algorithms assist in selecting the best seed nodes based on the marketing campaign's goals and constraints. We believe that the concept of combining the two marketing strategies into a unified approach can amplify the reach and impact of a marketing campaign. A combined approach will maximize the spread, engagement and impact of the campaign by leveraging both influential individuals and the organic sharing behaviour of seeds. We believe that there is no one size fits all and the specific algorithms and techniques chosen to be combined are dependent on the characteristics of the marketing campaign, the network structure, available data, and desired outcomes. Moreover, we believe that it would be interesting to see future research directed to a guideline outlining when certain seeding strategy algorithms and influence maximization models should be used in the joint approach. This may present as a regression model or decision tree structure where the objective is to develop a benchmark for marketing approaches based on specific variables such as characteristics of the marketing campaign, the network structure, available data, and desired outcomes to maximize the results of the campaign.

4.5 Applications of SMIs in Society

Future research directions in the applications of social media influencers in society could focus on further exploring the ethical implications of using social media data and influencers for various purposes. As the use of social media data becomes more prevalent in healthcare, crisis communication, supply chain management, and policy-making, it is essential to address concerns related to user privacy, data security, and potential biases in data collection and analysis. Researchers could delve into developing and implementing ethical guidelines and best practices to ensure responsible and transparent use of social media data and influencer marketing strategies.

Moreover, investigations into the impact of influencer marketing on consumer behavior and decision-making could provide valuable insights for businesses and policymakers. Understanding how influencers influence consumer perceptions, purchasing decisions, and brand loyalty in different societal applications can inform effective marketing strategies and enhance the overall effectiveness of influencer-driven campaigns.

Furthermore, there is scope for research on the long-term effects of influencer marketing in different sectors. Examining the sustainability and durability of the impact created by influencer-led initiatives can help in identifying the optimal duration and frequency of influencer campaigns for maximizing outcomes and return on investment.

As social media platforms and algorithms continue to evolve, future research could also explore the changing dynamics of influence and engagement between influencers and their followers. Investigating how platform changes affect the reach and impact of influencers, as well as how followers' behavior evolves in response to these changes, can provide valuable insights for adapting influencer marketing strategies to emerging trends and platform features.

Additionally, as the utilization of machine learning and AI technologies in influencer marketing grows, research on the interpretability and explainability of these algorithms is crucial. Understanding how machine learning models make decisions and how they can be interpreted can enhance trust and transparency in influencer marketing strategies, especially in domains like healthcare and crisis communication, where accuracy and accountability are paramount.

Usually, governmental organizations, health organizations, non-profits and other stakeholders with a social media presence have multiple social media accounts which they use to share information. An investigation into the platforms these organizations choose to use can suggest the importance placed on the different platforms. For example, if the International Committee of the Red Cross (ICRC), a global non-profit organization, has Facebook, Instagram and TikTok accounts, which one will people trust more during a disaster event (compared to daily usage for entertainment and communication purposes)? Will the average social media user follow the organization across all platforms or stick to one? Further, if multiple platforms are followed, where would they typically start and in which order will the other platforms be added?

It was observed that in the presence of natural disasters, crisis communication studies usually extract data from a single social media platform, typically Facebook [459] or Twitter [435, 467] to study the behaviour of people and how stakeholders (governmental organizations, health organizations, non-profits, etc) disseminate information to a population. We believe that examining this behaviour across multiple social media platforms can provide more valuable insights. Investigating matters such as which platforms people trust the most to receive crisis-related information can add tremendous value to the research community as well as positively impact humanitarian communication efforts. Even further, which platforms are believed to spread propaganda and not seen as credible to social media users in the event of a natural disaster or hazard-related crisis will help to target resources where they are most needed, reduce waste and maximize the communication budget.

It will also be interesting to compare the crisis communication styles of the organizations involved in natural disasters, public health crises and corporate brand crises for similarities and differences in persuasive communication techniques. The outcomes will allow us to understand how to better reduce the risk of a negative reputation, inappropriate behaviours, and preventable deaths (in the case of natural disasters and health crises). Furthermore, methods typically used in isolated situations may be found to be applicable to other scenarios.

Moreover, it was observed that as much as social media is used to study disaster management and health crisis communication, influencers are not used in these types of crisis communication. This may be because influencers are not trusted enough to provide essential information, especially when lives are at stake. Influencers may need to become advocates for a specific cause to be trusted for communicating information like disaster crisis communication. This leads to the curiosity surrounding who plays the role of the influencer in these scenarios. For example, in a hurricane event, do the meteorologists or the news anchors, who have personal social media accounts and often post updates, become the influencers? Must they be affiliated (tagged) with the official social media accounts of specific news outlets to gain credibility and be trusted? Or do the humanitarian organizations themselves, play the role of the influencer? Experiments involving automated text-mining and manual content analysis can be used to observe social media user behaviour toward the role of the influencer played by different parties during crisis events.

Virtual influencers created from computer-generated imagery (CGI) have gained large audiences as well as the attention of some brands. One of the most popular virtual influencers, Lu do Magalu has over 14.6 million followers on Facebook, 6 million followers on Instagram, 2.6 million YouTube subscribers and 1.3 million followers on Twitter and TikTok respectively [323]. She has been featured in product reviews, and unboxing videos and has also shared software tips for Magazine Luizaon, one of the largest retail companies in Brazil.

Future research may attempt to understand the appeal of virtual influencers to consumers and brands as well as the conditions for their success. It will be interesting to see academic research being conducted to assess whether current seeding strategies and influence maximization tactics have the same effect on virtual influencers in conditions previously tested with human influencers. Also, in scenarios of brand crisis, can virtual influencers be employed? Similarly, can they be utilized for crises involving natural disasters? Can they further change the way online selling is conducted to see a greater transformation in the way supply chain and retail via live streaming are conducted? Simply put, can virtual influencers replace human influencers and what circumstances would warrant this being effective?

The legislation relating to social media and SMIs is not up to date. We anticipate more conversations and academic research on areas such as ownership, copyright and intellectual property. It may interesting to see a union formed to standardize rates and contracts and research tackling the effects on the SMI domain. Laws concerning influencer contracts with brands, as well as terms and conditions of operations, are a growing concern in the industry. As such, we are interested in seeing academic research on SMIs expanded in this area. Disclosure laws have become a popular topic since the FTC and other regulatory bodies have mandated certain behaviours regarding posts. However, creator rights and other pivotal topics remain absent from conversations regarding regulation and studies on SMI policy.

Moving forward, we expect to see companies making in-house marketing efforts and generating UGC content instead of hiring external influencers to save costs and capitalize on building personal connections with their audience. We believe that the number of followers will have less significance in the criteria of being an influencer and that persons will be required to be experts in their field. This is because social media platforms are now competing with traditional search engines for knowledge sharing. In fact, some people prefer to search for specific information on TikTok instead of searching on Google. We expect that live streaming and selling products in real-time will increase since Amazon and Target have proven how successful the method is. However, a slight shift may be where more influencers become entrepreneurs and use live streaming to sell their personal products.

As more companies continue to reap the rewards of having influencers in the marketing budgets and working with them on specific deals, they may want to venture into more long-term relationships where influencers are hired as spokespersons for the brand as opposed to one-off contracts. It may be useful to investigate the distinct outcomes on consumer buying behaviour when long-term relationships with influencers are established, compared to short-term contract influencer relationships. Moreover, how does the effectiveness of influencer marketing campaigns differ when influencers are hired as brand spokespersons versus working on one-off contracts? Additionally, what are the benefits and challenges associated with having an influencer marketing department led by influencers with in-house creators? Also, how can SMI consultants effectively assist influencers in building their careers and securing brand deals? Finally, what are the key components and strategies for developing effective marketing plans for influencer-based marketing campaigns given these different circumstances?

Given the disjointed nature of SMI literature, we would like to know how the representation of social media influencers in marketing journals compares to their representation in operations research and management sciences literature? Furthermore, what are the distinct perspectives and insights that can be gained by integrating diverse academic literature on social media influencers from multiple domains? Moreover, how do social media influencers perceive their own roles and contributions in the context of marketing, management sciences, production and operations management, and other relevant fields?

Overall, academic research in the applications of social media influencers in society must continue to embrace interdisciplinary perspectives, combining insights from marketing, communication, social sciences, computer science, and ethics. By addressing these future research directions, scholars can pave the way for responsible and effective utilization of influencers and social media data to address societal challenges and opportunities in a manner that benefits individuals, organizations, and society as a whole.

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