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Going Viral for a Greener Future: How to Harness the Power of Active Viral Marketing in Green Product Campaigns

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Abstract

This study examines the effectiveness and potential benefits of active viral marketing over traditional viral marketing methods in promoting green products. This study identifies the factors that influence people's willingness to purchase green products and the impact of others on their purchasing decisions. In addition, this study proposes a more efficient approach by categorizing customers using demographic data to overcome computational challenges in active viral marketing. The present study contributes to the field of green marketing by demonstrating the potential of active viral marketing as an attractive method for marketing various green products. This study investigates the role of gender, academic degree, age, and favorite social network in the marketing of green products using active viral marketing. A descriptive survey method was adopted, and data were collected through library research, electronic sources, and a Likert scale questionnaire. Face validity and reliability were evaluated using Cronbach's α test. Data analysis and identification of factors affecting green product purchase were performed using the decision tree algorithm. The findings of this study provide valuable insights into the relationships among demographic variables, social network preferences, and various aspects related to green product marketing. No significant relationship was observed between gender and favorite social network, which is consistent with previous studies. However, there was a significant relationship between age and the favorite social network, indicating that they depended on each other. This study highlights the potential of active viral marketing to increase product acceptance rates and offers a more efficient approach through customer categorization based on demographic data. These findings impact marketers and practitioners in the development of targeted marketing campaigns for green products. This study contributes to our understanding of the effectiveness and relevance of active viral marketing in the context of green marketing. In conclusion, this study demonstrates the importance of active viral marketing in green product promotion. This study identifies the influence of demographic variables and social network preferences on people's willingness to purchase green products. The findings of this study provide valuable insights for marketers and contribute to the field of green marketing by showcasing the potential of active viral marketing as an effective marketing strategy for various products, including green products.

Keywords

Active Viral Marketing, Viral Marketing, Green Marketing, Green Product Purchase, People's Willingness to Buy, Influence of Others on Buying

1. Introduction

The role and importance of marketing strategies in organizational success are widely acknowledged. Marketing strategies play a pivotal role in shaping an organization's interactions with its environment, particularly its customers. Over time, marketing and its strategies have been significantly influenced by the prevailing technologies of their era. The emergence and rapid growth of information technology have brought about a complete transformation of marketing strategies. Therefore, numerous production, service, and other organizations now design and develop marketing strategies to effectively leverage the resulting competitive advantages derived from these technologies.

Customer behavior in online markets differs significantly from that in physical markets. Hence, organizations must develop a deep understanding of online markets and their unique characteristics to develop effective strategies and gain a competitive advantage. With the intensifying competition in advertising, brands face challenges in capturing consumers' attention, effectively conveying their message, and persuading them to make a purchase (Gallino et al., 2023). However, the widespread popularity and continuous growth of the internet have created a promising opportunity for marketers in the digital arena, as an increasing number of people are drawn to the online realm (Rappaport, 2007).

Viral marketing is a prominent marketing strategy and model in the age of technology. It builds upon the concept of word-of-mouth marketing, which involves consumers sharing their personal experiences with a product or company (Yeoh et al., 2013). The term "viral marketing" was initially introduced by Steve Jurvetson and Tim Draper at Hotmail in 1997 (Phelps et al., 2004). This innovative approach leverages the power of social networks and online platforms to amplify the reach and impact of marketing campaigns. The key to successful viral marketing campaigns is to get a company's network and contacts to do the hard work for it by recommending and sharing the company promotional offers to friends and colleagues, who in turn will recommend it to their friends and so on. An effective viral marketing campaign can get the company's marketing message out to thousands or even millions of potential customers at phenomenal speed. When the "Gangnam style" video by the Korean pop star, Psy, was launched in 2012 on YouTube, nobody could estimate the speed of spreading the song and the video on the YouTube channel. Within a few months, the music video had been seen by nearly 3 billion people worldwide on YouTube (Hollensen, 2020).

Although researchers generally concur on the concept of viral marketing, there are slight variations in the definitions provided. Viral marketing can be defined as the voluntary sharing of a compelling brand message from one person to another, with the aim of influencing and persuading the recipient to further disseminate it through the internet (Porter & Kramer, 2006). Howard (2005), on the other hand, describes viral marketing as marketing techniques that leverage social networks to enhance brand awareness or achieve various company objectives, including sales growth, through viral processes (Sharma & Sharma, 2015). These definitions highlight the power of viral marketing in harnessing the potential of online networks to amplify brand messages and achieve marketing goals.

Despite the widespread popularity of viral marketing, there is still limited understanding of the factors that influence its effectiveness, particularly in the context of social media. The success of viral marketing campaigns relies on the sender's capability to transform recipients into active promoters (Borges-Tiago et al., 2019). In recent decades, organizations have increasingly focused on environmental concerns, which have become a significant area of interest. This highlights the evolving priorities of organizations and the need to consider environmental factors in marketing strategies.

In recent decades, the prominence of environmental issues has led to a significant increase in the number of organizations adopting environmental protection systems (Lee, 2017). Green marketing encompasses more than just internal operations, such as the production of environmentally friendly products. It also involves considering the needs of customers and society, who increasingly demand eco-friendly products (Cherian & Jacob, 2012). While organizations still require green marketing strategies, their effectiveness has become paramount (Park & Ha, 2012). This highlights the importance of developing impactful green marketing strategies that align with customer demands and contribute to environmental sustainability.

Companies have several compelling reasons to embrace green marketing, including compliance with environmental pressures, gaining a competitive advantage, enhancing their image, accessing new market opportunities, and increasing the value of their products. Chen (2010) asserted that green marketing can elevate the unique and intangible value of a brand. To ensure the effectiveness of green marketing efforts, companies must integrate green marketing goals with organizational competitiveness, stakeholder attention, and business activities (Chen & Chen, 2019). This holistic approach ensures the quality and success of green marketing initiatives, enabling companies to reap the benefits of sustainable and environmentally conscious practices.

In recent decades, environmental concerns have emerged as a significant focus for organizations (Fernández et al., 2003). The prominence of environmental issues has led to a substantial increase in the number of organizations adopting environmental protection systems (Lee, 2017). Pollution is a consequence of the inefficient utilization of resources (Sun et al., 2021). As urbanization continues to increase, governments are increasingly prioritizing climate change and environmental protection (Chen et al., 2023). These factors highlight the growing importance of addressing environmental challenges and the need for concerted efforts from both organizations and governments.

Enhancing customers' knowledge about green products plays a crucial role in the success of green marketing (Reddy et al., 2023). Additionally, promoting environmentally friendly behavior among individuals contributes to the effectiveness of green marketing efforts (Do Paco et al., 2019). Viral marketing campaigns offer several advantages over traditional mass media activities, with the ability to target specific customer groups being the most significant advantage. This is because communication on social media platforms is often driven by shared interests (Razmerita et al., 2016). Given the rapid growth of technology and the increasing popularity of social networks, social media presents a promising platform for implementing successful green marketing strategies.

Viral marketing is a powerful marketing technique that leverages existing social networks to rapidly increase product awareness through a virus-like process. This method spreads online through word-of-mouth marketing, using the internet to reach several people quickly. Despite the significant importance of environmental issues, the adoption of green marketing by organizations has unfortunately been slow. However, viral marketing is an effective tool that can be used to accelerate green marketing efforts and widely introduce green products at a low cost. By harnessing the potential of viral marketing, organizations can leverage the power of social networks to promote environmental sustainability and drive the adoption of eco-friendly products.

In recent years, the expansion of information access and the development of advanced tools for storing and processing large-scale data have sparked a surge in research focused on analyzing the dynamics of information dissemination in real-world scenarios. This research aims to gain a deeper understanding of the factors that contribute to the success or failure of existing models in explaining these dynamics. Consequently, a new model of information dissemination, known as the active viral marketing model, has been proposed. This model better aligns with the requirements of commercial companies because it emphasizes the need for continuous marketing investments to effectively promote their products (Dwivedi et al., 2021). By embracing this active viral marketing model, companies can enhance their marketing strategies and leverage the power of information dissemination to achieve greater success in promoting their products and reaching their target audience.

The dynamics of information dissemination in viral marketing enable rapid product introduction to a large audience, facilitating faster customer feedback. With the rise of social networks, viral marketing has become a promising method for promoting various products. However, limited research has focused on the viral marketing of green products.

While studies have explored the acceptance of green products, reasons for purchasing them, and environmentally friendly behavior, little attention has been paid to the application of viral marketing in this context. Active viral marketing, which offers advantages over traditional methods, has not been used to advertise green products. This may be attributed to the complexity of active viral marketing calculations, which have remained largely theoretical. Furthermore, the influence of individuals on the active viral marketing algorithm has not been adequately addressed, despite their crucial role in spreading the message for viral dissemination.

1.1. The Aim of the Study

This study investigated and proposed a method for using active viral marketing to promote green products. This study addresses the limitations of traditional viral marketing methods and explores the potential benefits of active viral marketing in promoting green products. By examining the factors influencing people's willingness to buy green products and the influence of others on their purchasing decisions, this study seeks to provide insights into the effectiveness of active viral marketing in increasing product acceptance rates. In addition, this study aims to overcome the computational challenges associated with active viral marketing by proposing a more efficient approach through the categorization of customers using demographic data. Ultimately, this study aims to contribute to the field of green marketing by demonstrating the potential of active viral marketing as an attractive method for marketing various products, including green products.

1.2. Objectives

1) To investigate the role of gender in the marketing of green products using active viral marketing.

2) To investigate the role of academic degree in the marketing of green products using active viral marketing.

3) To investigate the role of age in the marketing of green products using active viral marketing.

4) To investigate the role of people's favorite social network in the marketing of green products using the active viral marketing method.

1.3. The Main Research Question

How can people be classified in terms of value in marketing green products using the active viral marketing method?

1.4. Sub-Research Questions

1) To what extent does gender influence people's willingness to buy green products in the context of active viral marketing?

2) To what extent does age influence people's willingness to buy green products in the context of active viral marketing?

3) To what extent does academic degree influence people's willingness to buy green products in the context of active viral marketing?

4) Which of the three factors, gender, age, and academic degree, has the greatest influence on people's willingness to buy green products in the context of active viral marketing?

5) To what extent does gender influence people's susceptibility to social influence in the context of buying green products using active viral marketing?

6) To what extent does age influence people's susceptibility to social influence in the context of buying green products using active viral marketing?

7) To what extent does academic degree influence people's susceptibility to social influence in the context of buying green products using active viral marketing?

8) Which of the three factors, gender, age, and academic degree, has the greatest influence on people's susceptibility to social influence in the context of buying green products using active viral marketing?

2. Literature Review

Active viral marketing is an innovative approach that uses algorithms to identify influential individuals within social networks and disseminate messages to them (Sela et al., 2018). The objective is to create a cascade effect that rapidly and efficiently reaches numerous people. Green marketing, on the other hand, involves promoting environmentally friendly or sustainable products or services (Arseculeratne & Yazdanifard, 2014). Green marketing campaigns often emphasize the environmental advantages of a product, such as reduced energy consumption or the use of recycled materials. Consequently, active viral marketing can serve as a potent tool for promoting green products (Nekmahmud et al., 2022). By targeting influential individuals in social networks, businesses can generate a cascade of messages that reach potential customers already interested in green products.

Using active viral marketing to promote green products offers several benefits, including the following:

- Reach: Active viral marketing enables the rapid and efficient dissemination of messages to a large audience (Sela et al., 2018). This is particularly valuable for green products, which may have a narrower target audience than traditional products.
- Credibility: Messages shared by individuals within social networks are often perceived as more credible than traditional advertising (Arseculeratne & Yazdanifard, 2014). This is crucial for green products, which are sometimes

viewed as more expensive or less effective than their conventional counterparts.

- Engagement: Active viral marketing can engage consumers more meaningfully than traditional advertising (Rollins et al., 2014b). This is especially important for green products because consumers may exhibit greater passion and interest in these products.
- Several factors influence the effectiveness of active viral marketing campaigns, including:
- Content quality: Content shared through active viral marketing campaigns must be of high quality, informative, and engaging (Sela et al., 2018). Consumers are more likely to share content that they find interesting and valuable.
- Target audience: Active viral marketing campaigns should target the appropriate audience (Rollins et al., 2014a). Businesses must identify individuals who are most likely to be interested in their green products and who are inclined to share messages within their social networks.
- Social media platform selection: Active viral marketing campaigns should be executed on appropriate social media platforms (Rollins et al., 2014a). Businesses need to identify the platforms where their target audience is most active.
- However, active viral marketing also presents challenges, such as:
- Identifying influential individuals: Businesses must be able to identify influential individuals within social networks to effectively target them with active viral marketing campaigns (Sela et al., 2018). This can be a challenging task that requires a thorough understanding of the target audience and social media networks.
- Cost: Active viral marketing campaigns can be costly as they require investment in campaign development and execution (Rollins et al., 2014a).
- Potential for negative feedback: Poorly executed active viral marketing campaigns may result in negative feedback from consumers, potentially damaging the business' reputation and hindering future marketing efforts for green products (Sela et al., 2018).

2.1. Viral Marketing

Viral marketing is a marketing strategy that creates and distributes content with the intention of rapid and extensive dissemination, akin to the spread of a virus. This approach capitalizes on the use of social networks and online platforms to amplify the reach and impact of marketing messages. The primary objective of viral marketing is to generate buzz and stimulate word-of-mouth promotion, ultimately leading to heightened brand awareness, increased customer engagement, and adoption of products or services (Wilson, 2000).

In viral marketing, the content itself is meticulously crafted to be highly shareable and captivating, often incorporating elements such as humor, emotion, surprise, or controversy (Berger, 2013). When individuals encounter such content, they are compelled to share it within their social networks, resulting in exponential growth in its reach and exposure. Organic sharing and distribution extend the message reach far beyond the initial target audience.

Viral marketing campaigns can manifest in various forms, including videos, images, memes, interactive games, and social media challenges (Hennig-Thurau et al., 2013). Social media platforms, online communities, and email sharing serve as common channels for disseminating viral content. By creating compelling content that resonates with the intended audience, viral marketing can generate substantial attention, engagement, and brand exposure, often at a relatively low cost compared with traditional advertising methods (Bampo et al., 2008).

However, not all marketing campaigns can achieve viral success. The success of viral marketing hinges upon a combination of factors, including the quality and relevance of the content, timing, targeting, and the audience's willingness to share (Kaplan & Haenlein, 2011). Nevertheless, when executed effectively, viral marketing can generate significant brand visibility and exert a profound influence on consumer behavior.

2.1.1. Advantages and Disadvantages of Viral Marketing

Advantages of Viral Marketing:

1) Cost-effectiveness: Viral marketing proves to be more cost-effective than traditional advertising methods, such as television networks and print ads, as it eliminates the need for expensive media fees and physical distribution.

2) Influence of Social Media: Viral marketing capitalizes on the active user base of social media platforms, particularly among the younger generation, who are more influenced by influencer advertising than traditional ads (Duffett, 2017).

3) Hidden Marketing Opportunities: Viral marketing can employ hidden marketing techniques, where influences promote a product without explicitly disclosing their financial motivations. This approach creates a perception of genuine endorsement, enhancing its effectiveness (Ekström & Hjort, 2009).

Disadvantages of Viral Marketing:

1) Lack of Control: Viral marketing campaigns inherently lack control once they are released to a wide audience. Errors or criticisms identified by users become difficult to reverse, potentially impacting the company's brand image (Cruz & Fill, 2008).

2) Loss of Control over Distribution and Recipients: Viral marketing campaigns lose control over the distribution of promotional messages and the identities of recipients. The dissemination of content is driven by individuals and groups, which can result in the message reaching unintended or unrelated audiences (Miller & Lammas, 2010).

2.1.2. Basics of Viral Marketing

Viral marketing operates on six fundamental principles to achieve maximum success (Wilson, 2000):

1) Free Products or Services: Offering complimentary goods or services in exchange for sharing information entices potential customers and stimulates growth.

2) Hassle-Free Sharing: Facilitating easy content sharing on online platforms ensures maximum reach, with concise messages being preferred.

3) Scalability: Maintaining adequate server capacity is crucial to handle the increased traffic and demand generated by word-of-mouth advertising.

4) Leveraging Motivational Factors: Incorporating elements of excitement, popularity, likability, and comprehension into advertising messages enhances their effectiveness.

5) Using existing networks: Sharing viral content within social network amplifies message distribution.

6) Leveraging resources: using popular social media platforms taps into their infrastructure and reach, expanding the campaign's audience.

2.1.3. Emotions in Viral Marketing

The emotions conveyed in viral marketing messages play a crucial role in their success (Fill & Turnbull, 2019). Here are six key emotional states that drive viral behavior (Duhachek et al., 2007):

1) Surprise: Unexpected elements in marketing messages have a significant impact on the audience, but combining surprise with other emotions proves to be more effective.

2) Joy: Happiness, a positive emotion, is commonly used in marketing to create a fun and interactive brand image or promote products that enhance consumers' well-being.

3) Discomfort: Discomfort, a negative emotion, can elicit swift responses to unfortunate events. However, balancing discomfort with hope for change is crucial for sustained engagement.

4) Anger: Anger, another negative emotion, can provoke strong reactions in marketing messages, particularly in response to perceived injustices. It often generates short-term effects.

5) Fear: Fear is often used in marketing campaigns, especially in political contexts. It can evoke a short-term commitment to addressing perceived threats, but its use requires caution.

6) Disgust: Disgust is employed to target specific audiences, particularly males, and emphasize rebellion or nonconformity. Men tend to share more messages containing disgusting jokes than women.

2.1.4. External Drivers for Promoting Viral Marketing

The speed of viral message dissemination is significantly influenced by external factors. One major driver is the endorsement of content by media platforms or popular internet personalities with a substantial following (Berger & Milkman, 2012). A notable example is Reddit, an online hub where users share content across various topics within specific communities (Analytical Study on (Reddit, 2018)). For instance, Reddit's r/AskReddit community invites diverse questions and receives answers from experts in different fields. The visibility of these answers is determined by their ranking based on relevance, rationality, and entertainment value. With 330 million monthly active users and 138,000 communities, securing a spot on Reddit's front page exposes content to millions of people, amplifying its reach (Pandrekar et al., 2018).

Another example is YouTube's most viewed video section, which serves as a repository of trending content, including unexpected entries such as viral marketing clips. The selection criteria for this list include broad appeal, avoidance of misleading or clickbait content, coverage of diverse global topics, and novelty. Factors such as views, rate of view acceleration, source of views, and video longevity are also considered. However, the final decision on which videos make the cut rests with the programing team. These external forces, such as Reddit's bandwagon effect and YouTube's most viewed list, play a significant role in accelerating the dissemination of viral marketing messages (Kwon & Park, 2023).

2.1.5. Successful Viral Marketing Campaigns

Over the past decade, numerous successful viral marketing campaigns have emerged, highlighting the effectiveness of online marketing. However, quantifying the success of viral marketing campaigns solely based on tangible achievements poses challenges because success is subjective and contingent upon the context and predefined objectives. Therefore, success can be gaged by the impact on audience comprehension, as evidenced by the number of searches conducted during the design phase of interviews in a particular study (Business Dictionary, 2018).

Several highly successful viral marketing campaigns have gained significant traction, accumulating millions of views on platforms such as Facebook and YouTube. One of the successful viral marketing campaign is Melbourne Metro's "Stupid Ways to Die" from 2012. This campaign utilized a catchy music video to raise awareness about subway safety. It garnered a staggering 165 million views on YouTube (YouTube Marketing, 2023). Also, the ALS Ice Bucket Challenge is yet another notable viral campaign. Aimed at raising funds for ALS research, it resulted in 115 million donations and reached over 440 million people worldwide (YouTube Marketing, 2023). These examples demonstrate the power of viral marketing campaigns in reaching a wide audience, generating significant engagement, and making a lasting impact.

2.1.6. Related Frameworks in the Field of Viral Marketing

To gain a comprehensive understanding of viral marketing, it is crucial to examine foundational marketing frameworks and theories. Researchers have developed structured interviews to explore the applicability of established marketing theories to online platforms and user communities (Fill & Turnbull, 2019). One notable framework is Porter's theory of competitive advantage, which analyzes various business strategies and emphasizes a business' relative position compared to competitors within an industry. A sustainable competitive advantage can be achieved through cost leadership or differentiation, while a focus strategy targets specific market segments (Fill & Turnbull, 2019).

In the context of viral marketing, focus and differentiation are of utmost importance. Creating value and delivering engaging content that surpasses competitors' leads to increased exposure and audience engagement. Differentiating oneself by producing valuable and captivating content aligned with audience interests is crucial (Fill & Turnbull, 2019). In addition, creative marketing communication plays a vital role. Creative advertising captures audience attention and enhances campaign effectiveness by challenging expectations and promoting innovative ideas. Distinctiveness and relevance are fundamental, with distinctive advertising leading to deeper cognitive processing, increased reception, and revisit rates. Relevance ensures that the campaign holds meaning for the audience. Understanding cultural aspects and environmental creativity is critical in the online environment. Cultural narratives, such as memes, significantly influence the success of viral marketing campaigns. Creativity plays a vital role in determining advertising impact and the likelihood of content sharing (Fill & Turnbull, 2019).

2.1.7. Models of Information Dissemination in Viral Marketing

Mathematical models have been extensively used by epidemiologists to study the transmission of diseases, forecast future outbreaks, and develop effective strategies for epidemic control (Anderson & May, 1992). The success of these models in understanding disease outbreaks has led to their application in other domains, including the adoption of new products and dissemination of information. The dynamics of information dissemination in social networks have been the subject of extensive research, resulting in the proposal of numerous mathematical models to elucidate these dynamics. An important aspect of information dissemination is the identification of influential nodes to maximize the acceptance of products or ideas within the network. Prevalence models are generally classified into two types: collective and individual models. Collective models consider the entire interconnected society, where interactions and contagion can occur between various components. Conversely, individual-based models focus on network structures that depict potential interactions between individuals (Sela et al., 2018).

Collective models assume a fully interconnected population in which any pair of individuals can interact and spread a message. This implies a homogeneous population in terms of communication and the likelihood of interaction. These models allow for the observation of various collective phenomena, such as population size and the rate of expansion at different transitional periods (Anderson et al., 1992). One of the most practical models for expansion computation is the SIR model (Anderson et al., 1992). This model divides the population into three groups: susceptible, infected, and recovered. The SIR model can be employed to simulate the spread of viral marketing campaigns by considering the susceptible population as individuals, the message as the infection, and the recovered population as individuals who have seen the message and are no longer interested in it.

Individual-based models assume a network structure that describes potential interactions (network edges) between individuals (network nodes). In contrast to collective models, individuals can only be infected by their neighbors in the network and not by any member of the infected population. The linear threshold model (Granovetter, 1978; Kempe et al., 2003) is a fundamental individual-based model used to describe the spread of information on social networks. Another well-studied individual-based information dissemination model is the independent cascading model (Goldenberg et al., 2001). The Bass-SIR model, a noteworthy person-based model, was proposed by Fitch in 2016 (Mahajan et al., 1990). Independent linear and cascading threshold models have been employed in various studies. In addition, over the years, several techniques have been proposed to adapt these models to specific situations. Kempe et al. (2003) introduced two models to combine them into a unified framework.

2.1.8. Maximizing Information Penetration in Social Networks, Regarding Viral Marketing

The identification of influencer nodes plays a crucial role in maximizing the dissemination of information within social networks (Sela et al., 2018). The objective is to strategically activate a subset of nodes, referred to as seeds, to achieve the highest possible viral spread throughout the network. Various models and optimization techniques have been employed to define this objective, such as maximizing the number of receivers within a given time or budget constraint or minimizing the actions required to reach a specific number of receivers (Ye et al., 2022). In modern marketing, social networks are extensively used to analyze the market and develop targeted advertising strategies. Unlike traditional broad-based marketing approaches, social media analysis focuses on micro-segmentation and uses detailed information about individual users (Etlinger, 2014). The aim is to influence public opinion through targeted persuasion by leveraging viral transmission processes (Sela et al., 2018).

Identification of influencer nodes remains an active area of research. Although some nodes are effective based on historical data, the task is not always straightforward. Recent studies have explored new algorithms and models that use machine learning, particularly in the field of network science. Machine learning algorithms can be trained on historical data to learn patterns of information dissemination within a given network, enabling the identification of influential nodes. Network science provides models that consider the complex structure of social networks, resulting in more accurate and efficient identification of influential nodes (Sun et al., 2023).

1) Initial node selection for maximum impact

The identification of influential nodes in a social network relies on network-based metrics, such as centrality measures. Metrics such as degree, PageRank, betweenness centrality, and eigenvector centrality quantify a node's importance based on its connections. However, degree-based measures have limitations because they only consider the influence of immediate neighbors and overlook higher-degree connections. The effectiveness of early influencer strategies depends not only on network topology but also on information dissemination dynamics. Kempe et al. (2003) investigated the maximum penetration problem using linear threshold and independent cascade models. They demonstrated the problem's complexity and introduced a computationally expensive greedy algorithm that provides an approximate optimal solution.

The greedy algorithm is a simple and straightforward approach to influencer identification. It works by initially selecting a few nodes with high centrality measures and then iteratively selecting nodes that are most likely to influence the selected nodes (Chen et al., 2010). However, the greedy algorithm can be inefficient and inaccurate, especially for large networks. CELF and CELF++ are improved versions of the greedy algorithm that address some of its limitations. CELF uses a more sophisticated method for evaluating the influence of nodes, while CELF++ further improves the efficiency of CELF by using a more efficient data structure. Experimental evaluations have shown that CELF and CELF++ outperform the greedy algorithm in terms of accuracy and efficiency. For example, a study by Goyal et al. (2011) found that CELF++ was up to 10 times faster than the greedy algorithm while achieving comparable accuracy.

Other algorithms, such as the one proposed by Chen et al. (2010), have also been proposed to improve the efficiency of the greedy algorithm. However, CELF and CELF++ are two of the most popular and well-studied improved greedy algorithms for influencer identification.

Researchers have also focused on maximizing the impact within a budget or minimizing the number of actions required to infect a specific number of nodes. These problems are known to be NP-hard, but improved greedy algorithms with small errors have been proposed. Efficient algorithms have also been designed to achieve full coverage by infecting the entire network. Kempe et al. (2003) identified three dimensions in the maximum penetration problem: the number of initially activated nodes, the expected number of active nodes at the end of the diffusion process, and the time required for the diffusion process. By optimizing one or two of these dimensions, approximate algorithms can effectively solve the problem. Selecting an initial set of individuals for maximum impact is a complex task that necessitates various approaches and algorithms. The choice of approach depends on the specific network, desired outcomes, and available resources. Nonetheless, significant progress has been made in recent years, providing effective algorithms for identifying influential nodes in social networks.

2) Adaptive strategies for maximizing penetration

While most studies on information diffusion in social networks focus on selecting a subset of nodes to maximize the total number of activated nodes when all nodes are simultaneously activated at the start, recent research has introduced adaptive strategies that expand node selection over time. These strategies assess the contribution of each node to the overall adoption rate at each time step. There are two-step frameworks for maximizing impact. The first step involves selecting initial nodes for activation, whereas the second step involves selecting additional nodes at each time step to maximize activations in subsequent steps. The authors introduce an intermediate state, "available", which represents nodes whose neighbors are active. The goal in the first step is to select nodes that maximize the number of available nodes in the second step (Zhao et al., 2020).

The cascading model is a popular model for information diffusion in social networks. In this model, nodes are activated with a certain probability when their neighbors are activated. However, in practice, node activation can fail with a certain probability. To address this challenge, Tang & Wu (2017) proposed an adaptive strategy for the cascading model. In their strategy, the selected initial nodes are released in batches over time. After each batch is released, the authors consider the previous infection attempts when selecting nodes for the next batch. This helps to improve the overall adoption rate of the information.

Adaptive strategies offer advantages over traditional strategies by considering the dynamic nature of social networks and adjusting the node selection process over time. By continuously evaluating the impact of selected nodes and incorporating new information, adaptive strategies can more effectively maximize information penetration.

Overall, the field of maximizing information penetration in social networks is rapidly advancing. Researchers are developing innovative algorithms and strategies that use machine learning, network science, and adaptive approaches to identify influential nodes and optimize the spread of information. These advancements have implications for various fields, including marketing, public health, and social activism, where effective information dissemination is crucial for achieving desired outcomes.

2.1.9. Types of Viral Marketing

Viral marketing campaigns can be categorized into two distinct types: active and passive (Berger, 2013). These categories outline different approaches to initiating and disseminating viral content:

- Active viral marketing campaigns involve intentional efforts by marketers or businesses to promote viral content. Marketers employ a variety of strategies, such as creating engaging videos, launching social media campaigns, or collaborating with influencers, to amplify the reach and impact of the content. This deliberate and strategic approach encourages individuals to actively share and engage with the content.
- Passive viral marketing campaigns occur when viral content spreads organically and autonomously without direct involvement from marketers or businesses. In this case, the content itself possesses inherent shareability and resonates with the audience, compelling them to share it willingly. The success of passive viral marketing campaigns often relies on the content's appeal,

whether it is entertaining, emotionally impactful, or useful. When content strikes a chord with the audience, they spontaneously share it within their networks, leading to its viral dissemination.

Both active and passive viral marketing approaches can effectively generate buzz and enhance brand awareness. Active viral marketing grants marketers greater control over the content and its distribution, enabling them to actively initiate and promote it to achieve their desired outcomes. Conversely, passive viral marketing relies on the content's inherent shareability and appeal, allowing it to propagate naturally and gain traction without direct intervention. However, this does not mean that marketers are entirely passive in passive viral marketing campaigns. They can still strategically plan and optimize their content to maximize its virality.

2.2. Active Viral Marketing Models

Active viral marketing models are a highly effective strategy for businesses to quickly reach a large audience with their message. These models utilize the power of social networks and the influence of individuals. The process involves identifying key individuals, known as "seeds", who share the message or product with their network, triggering a chain reaction of sharing. This exponential spread helps achieve various goals, such as enhancing brand recognition, generating leads, boosting sales, and introducing new products or services. Implementing active viral marketing models is more cost-effective than traditional marketing campaigns because it primarily involves identifying and seeding influential individuals. However, identifying the right seeds and developing an engaging message or product are essential for success (Van den Bulte, 2011).

2.2.1. Maximum Penetration in Active Viral Marketing

Maximizing the spread of information in viral marketing models is a challenging task. To address this issue, researchers have proposed the SSH algorithm. This algorithm selects the most influential nodes in a network and activates them iteratively, recalculating the influence scores of the nodes after each step. While effective, the SSH algorithm can be computationally expensive for large networks (Goyal et al., 2011).

- Model Description: Scoring Formula for Identifying Influencers:

The viral marketing method uses a scoring formula to identify the most influential individuals. This formula combines an individual's influence (their likelihood to adopt a product or service) and social influence (influence from peers who have adopted similar products or services). The social impact score helps identify individuals with the greatest influence on their peers (Ahlberg, 2018).

2.2.2. Asch Model

The Asch conformity experiments, conducted by Solomon Asch in the 1950s, investigated how social pressure affects people's tendency to conform to the majority opinion. Participants were asked to compare the lengths of lines, and confederates gave incorrect answers on purpose. The experiments showed that approximately 32% of participants conformed to the incorrect majority opinion at least once, and approximately 75% conformed at least once over 12 trials (Asch, 1956). These experiments demonstrate the power of social pressure, even when people know that the majority is wrong. The findings stress the importance of understanding how social factors influence decision-making and critically evaluating information.

In the context of viral marketing, the active viral marketing model uses the threshold and probability function Pro to model how social pressure affects individual behavior. The threshold determines how much social pressure is needed to make people conform, while the probability function Pro calculates the likelihood of an individual conforming to the majority opinion based on their social and individual influences.

The Asch conformity experiments provide evidence that the threshold and probability function Pro are crucial factors in influencing individual behavior during viral marketing campaigns. For example, the experiments suggest that a larger majority and individual uncertainty about their own opinion make it easier for people to conform. Therefore, effective viral marketing campaigns should focus on large groups and present information in a way that makes people unsure of their own opinions. In summary, the Asch conformity experiments offer valuable knowledge about social factors that influence individual behavior, which can be used to create more effective viral marketing campaigns (Asch, 1956).

- Factors Influencing the Asch Conformity Test

The experiments found several important factors that influence the Asch conformity test:

- Social status: People with higher social status are more likely to conform to the opinions of those with lower social status, seeing them as more powerful and influential.
- Group size: The number of people in a group affects conformity. Compliance increases with group size up to a certain point. Compliance rates were 3% with one person, 13% with two people, and up to 32% with three or more people. Beyond three people, increasing the group size does not significantly increase compliance.
- Lack of information: People are more likely to conform when they have little information about a topic, relying on the opinions of others to make up for their own lack of information.

These factors show how social status, group size, and information availability affect how people conform to majority opinions in the Asch test.

- Additional Notes:

1) The Asch conformity experiments have been criticized for being unethical and not reflecting real-world situations. However, they have been replicated numerous times and have consistently yielded similar results across different pop-

ulations and cultures.

2) The experiments have been praised for their insights into social factors that influence human behavior. They have shown that people are more likely to conform in group settings when they are unsure about their own opinions or when they are faced with individuals of higher social status.

3) The findings of the Asch conformity experiments have practical applications in various fields, such as jury decision-making, consumer behavior, and political campaigning.

2.2.3. Comparison of Active Viral Marketing Algorithms with Other Algorithms

Active viral marketing (AVM) algorithms are a novel approach to promoting product adoption on social media. They operate by repeatedly selecting nodes (people) to activate, maximizing the spread of information through social networks. AVM algorithms outperform traditional methods by considering the social structure of the network and the probability of individuals being activated. Studies have shown that AVM algorithms can increase product adoption rates by up to 75% (Rollins et al., 2014b).

Special vector centrality (SVC) is an emerging measure of influence on social media that has been shown to be more accurate than traditional measures, such as degree centrality. AVM algorithms that incorporate SVC have been shown to further improve product adoption rates. For example, a study published in Social Networks in 2021 found that an AVM algorithm that used SVC outperformed a degree-based AVM algorithm by 30% in terms of product adoption (Chen & Zhang, 2022).

These findings demonstrate the potential of AVM algorithms to revolutionize viral marketing campaigns. By incorporating SVC, marketers can more effectively identify influential individuals in social networks and target them with tailored marketing messages, ultimately leading to increased product adoption rates (Chen & Zhang, 2022).

2.2.4. Impact of Time on Active Viral Marketing

Time plays a crucial role in active viral marketing (AVM) campaigns. While it is essential for the spread of information and product adoption, it can also lead to a decline in effectiveness over time.

Positive Impacts of Time on AVM

- Increased reach and exposure (Jin et al., 2023);
- Greater brand awareness and engagement (Rollins et al., 2014b);
- Improved product adoption rates (Chen & Zhang, 2022).

Negative Impacts of Time on AVM

- Decreased novelty and excitement;
- Increased skepticism and resistance;
- Saturated market.

Mitigation Strategies

- Freshness and creativity;
- Personalization and targeting;
- Limited time offers.

In conclusion, marketers should carefully consider the impact of time on their AVM campaigns and implement strategies to mitigate the negative impacts (Rollins et al., 2014b).

2.3. The Leybman Test: Assessing Social Media User Types

This test is a quiz designed to evaluate individuals' social exchange preferences. Social exchange theory suggests that people evaluate the costs and benefits of a relationship before deciding to engage with others (Leybman, 2013). This test categorizes individuals into four distinct groups based on their social behavior:

1) Altruists: Altruists are individuals who selflessly assist others without expecting anything in return.

2) Cooperators: Cooperators are individuals who are willing to help others if they anticipate receiving something in exchange.

3) Individualists: Individualists are solely concerned with their own benefits and do not prioritize assisting others.

4) Competitors: Competitors perceive others as obstacles and are determined to do whatever it takes to achieve personal success.

Alignment with Social Media Behavior:

Research has demonstrated that social media users exhibit behaviors consistent with social exchange theory. For instance, users who like other people's posts are more likely to receive likes on their own posts. This is because liking is a low-cost activity that can yield high-value rewards, such as increased social status and influence (Leybman et al., 2011).

Application of the Leybman Test:

The Leybman test can be employed to gain insights into how individuals utilize social media to establish and maintain social connections. Altruists may use social media platforms to connect with others and provide support, while competitors may employ social media to compete for attention and status. This test offers an enjoyable and straightforward approach to understanding one's interactions on social media. Moreover, it serves as a valuable tool for comprehending human behavior in both online and offline environments (Surma, 2016).

2.4. Green Marketing

Green marketing refers to the application of marketing principles and techniques to promote environmentally friendly and sustainable products and services. Its objective is to reduce pollution, conserve resources, save money, and attract customers who prioritize environmental concerns. Various strategies can be employed in green marketing, including:

1) Development and promotion of products made from recycled or biodegradable materials.

2) Designing energy-efficient and water-saving products.

3) Minimizing packaging and utilizing sustainable materials.

4) Encouraging sustainable practices among customers.

5) Allocating a portion of sales to support environmental organizations.

Incorporating green marketing into a business's sustainability strategy is essential. It not only helps protect the environment but also reduces costs and attracts environmentally conscious customers (Dangelico & Vocalelli, 2017).

2.4.1. Consumer Behavior towards Green Products

In recent years, consumers have shown a growing concern for the environment and a desire to make more sustainable choices (Lee, 2017). This shift in consumer behavior presents an opportunity for marketers to develop effective marketing campaigns that align with consumers' civic values. By emphasizing the environmental and social benefits of their products and services, marketers can tap into this trend and attract environmentally conscious consumers (Cherian & Jacob, 2012).

2.4.2. Green Social Behavior

Green social behavior refers to pro-environmental actions driven by social factors, such as the desire to assist others or conform to social norms. It holds significant importance as it contributes to achieving environmental sustainability. Organizations can foster green social behavior among their employees and customers through various initiatives, including offering green commuting options, providing educational resources on environmental issues, donating to environmental causes, implementing company-wide sustainability programs, and recognizing and rewarding employees for their green social behavior (Gatersleben et al., 2002).

Consumers place value on green products due to their environmental benefits, social implications, and perceived quality (Haws et al., 2014). Businesses can capitalize on this value by developing and marketing high-quality, affordable green products, educating consumers about their advantages, and ensuring their accessibility. Green behavior in shopping encompasses purchasing fewer products, selecting items made from sustainable materials, avoiding excessive packaging, buying locally, and supporting companies committed to sustainability. Businesses and consumers can collaborate to promote green behavior by developing and marketing green products, educating consumers, and making sustainable choices (Peattie, 2010).

2.4.3. Factors Influencing Green Behavior in Shopping

Several factors influence green shopping behavior, including environmental concerns, perceived effectiveness of sustainable purchases, personal values and norms, trust, and environmental knowledge. Businesses can encourage green behavior by developing and marketing sustainable products and services, ensuring their accessibility, educating consumers about their benefits, and collaborating with environmental organizations. Consumers can promote green behavior by purchasing fewer products, choosing sustainable options, avoiding excessive packaging, buying locally, and supporting sustainable businesses (Peattie, 2010).

Social networks play a crucial role in the viral marketing of green products. They provide businesses with a platform to reach a wide audience through engaging content and connect with influencers who can amplify their message. Successful viral marketing campaigns for green products focus on creating informative, relevant, and emotionally resonant content (Berger & Milkman, 2012). Additionally, they target the appropriate audience using social media analytics to micro-segment and identify influential nodes (Li et al., 2021).

Here are a few examples of successful viral marketing campaigns for green products:

1) Patagonia's "Don't Buy This Jacket" campaign encouraged consumers to reconsider purchasing new clothes and instead repair and reuse their existing garments. The campaign garnered over 10 million views on YouTube and contributed to a 30% increase in Patagonia's sales (Rollins et al., 2014b).

2) The Body Shop's "Forever against Animal Testing" campaign raised awareness about animal testing in the cosmetic industry and urged people to choose cruelty-free products. The campaign utilized social media to share videos and testimonials from celebrities and activists, accumulating over 8 million views on YouTube (Ganatra et al., 2021).

3) Tesla's "Referral Program" offers discounts to customers who refer their friends and family to purchase a Tesla car. The program has been highly successful, generating over 100,000 referrals in 2019 (Marketing strategy website).

In conclusion, the adoption of green products is a crucial step in environmental conservation, addressing a critical issue in today's world. Social networks wield significant influence over consumer purchasing decisions, making an effective social media marketing strategy essential for environmentally friendly companies to promote the use of green products.

2.5. Conceptual Framework of Active Viral Marketing in Green Product Purchase

2.5.1. Predictors of Active Viral Marketing in Green Product Purchase

The predictors of active viral marketing in green product purchase can be categorized into three main groups:

1) Influential elements on people's willingness to buy (WTB);

2) Influence of others on individual purchasing decisions (SOI);

3) Demographic factors.

2.5.2. Influential Elements on People's Willingness to Buy (WTB)

These are the factors that directly influence a person's decision to purchase a green product. They include:

- Perceived environmental impact;
- Product quality;
- Price;

- Brand reputation;
- Social norms.

2.5.3. Influence of Others on Individual Purchasing Decisions (SOI)

These are the factors that indirectly influence a person's decision to purchase a green product through the influence of others. They include:

- Word-of-mouth;
- Social media;
- Celebrity endorsements.

2.5.4. Demographic Factors

These are the personal characteristics of the individual that may influence their decision to purchase a green product. They include:

- Gender;
- Age;
- Academic degree;
- Favorite social network.

The dependent variable in this framework is the active viral marketing in green product purchases, which can be measured by:

- Number of times a person shares information about a green product on social media;
- Number of times a person recommends a green product to friends and family;
- Number of times a person purchases a green product.

2.5.5. Relationships between Variables

The independent variables (WTB, SOI, and demographic factors) are expected to have a positive relationship with the dependent variable (active viral marketing in green product purchases). This implies that individuals who are more willing to buy green products and are more influenced by others are likely to have a higher active viral marketing score.

Demographic factors are expected to moderate the relationship between the independent and dependent variables. This means that the strength of the relationship may vary based on the individual's demographic characteristics. For example, younger people may be more inclined to share information about green products on social media compared to older individuals.

2.5.6. Research Model

The following research model can be used to test the conceptual framework:

Active viral marketing score in green product purchase = f (WTB, SOI, demographic factors). Where:

- Active viral marketing score in green product purchase = dependent variable;
- WTB = influential elements on people's willingness to buy;
- SOI = influence of others on individual purchasing decisions;
- Demographic factors = gender, age, academic degree, and favorite social network.

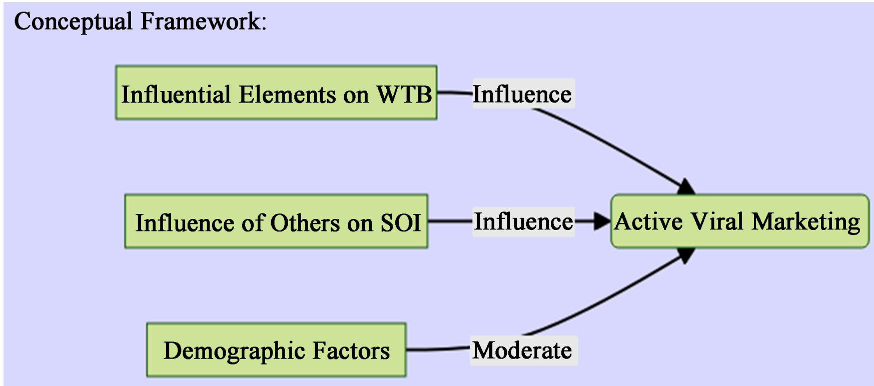

Figure 1. Conceptual framework.

3. Methodology

The research titled "Using Active Viral Marketing in Advertising Green Products" explores the relationship between viral marketing and green product marketing strategies. This study adopts an applied research approach with a descriptive-survey method.

1) Sample Size:

The statistical population consists of potential and actual customers of green products, with an unlimited population size. The sample size of 99 participants was determined using the Cochran formula. Although 104 individuals completed the questionnaire, it is important to note that a larger sample size generally contributes to increased accuracy in research findings. However, it's worth considering other factors such as sampling techniques and representativeness of the sample, which can also impact the accuracy of the results.

n = \frac{Z^2 \cdot P \cdot (1 - P)}{E^2}

E = 1% (0.01) - desired margin of error (in decimal form)

P = 0.5 - estimated proportion

Z = 1.96 - Z-value for a 95% confidence level

n =? - sample size

Substituting these values into the formula:

n = \frac{1.96^2 \cdot 0.5 \cdot (1 - 0.5)}{0.01^2}= 99

2) Data Collection Methods:

- Library research: Gather information from books, articles, online resources, and similar studies related to green marketing.
- Search through electronic sources: Access findings from studies conducted worldwide.
- Field study using a questionnaire: Design a questionnaire based on the Likert scale to collect data on influential elements for people's willingness to buy (WTB) and the influence of others on individual purchasing decisions (SOI). Include demographic questions about gender, age, academic degree, and favorite social network.

3) Questionnaire Validation:

- Face validity evaluation: Experts and individuals assess the relevance and appropriateness of the questionnaire.

- Reliability assessment: Calculate Cronbach's α to measure internal consistency. Values above 0.7 indicate acceptable reliability.
- Distribution: Use a Google Form for questionnaire distribution, employing simple random sampling.

4) Data Analysis:

- Decision tree algorithm: Specifically, the ID3 algorithm is used to analyze the data and identify factors affecting green product purchase.
- Decision tree advantages: Provides a visual representation of variable relationships, aids in understanding factors influencing active marketing score in green product purchases.
- Decision tree limitations: Exponential growth in size as problem size increases, reliance on single feature branching at nodes.

5) Questionnaire Reliability Assessment:

- Calculate Cronbach's α using SPSS software separately for WTB and SOI sections.
- WTB section: Cronbach's α of 0.754 indicates acceptable reliability.
- SOI section: Cronbach's α of 0.816 indicates acceptable reliability.
- Results can be generalized to the entire population.

6) Questionnaire Scoring and Analysis:

- Likert scale questionnaire: Use scores to categorize data based on a single criterion.
- Calculate individual scores for WTB and SOI sections by summing and standardizing scores.
- Obtain overall scores by averaging WTB and SOI scores for each individual.
- Analyze data using RapidMiner Studio software, drawing a decision tree based on overall scores and the Leybman test as separate target variables.

7) Leybman Test and Interactions:

- Second part of the questionnaire: Focuses on WTB, SOI, and the Leybman test to understand interactions among individuals.
- Leybman test categorizes individuals into four groups based on willingness to interact and communicate with others.
- Predicts personality type and likelihood of engagement in communication and interaction.

8) Decision Tree and Green Product Purchase:

- Decision tree as a visual representation of possible outcomes based on choices.
- Use decision tree to analyze data and identify factors influencing green product purchase.
- Decision tree advantages: Simplicity, handling of large and complex datasets, potential for combination with other decision-making techniques.
- Decision tree limitations: Exponential growth in size with problem complexity, single feature branching at nodes.

9) Target Market Understanding:

- Questionnaire includes demographic questions to understand and segment the target market.
- Gender, age, academic degree, and favorite social network are included.
- Data can be used to develop targeted marketing campaigns and improve marketing effectiveness.

Overall, this comprehensive methodology involves an applied research approach with a descriptive survey, utilizing various data collection methods, questionnaire validation, decision tree analysis, and understanding of the target market.

4. Results

The data analysis phase involved the use of specific statistical methods to prepare the collected data for comparison and analysis of the research hypotheses. Descriptive statistical methods were employed to summarize and organize the data, whereas inferential statistical techniques were used to draw conclusions about the target statistical population.

As it is mentioned in the Table 1, the study included 104 participants, with 45.2% being males and 54.8% females. In terms of social network preference, 61.5% of participants chose Instagram, while 38.5% opted for Twitter.

Table 1. Demographic Information.

Demographic Information of Study Participants	
Demographic	**Participants**
Gender	
Male	45.2%
Female	54.8%
Social Network	
Instagram	61.5%
Twitter	38.5%
Academic Degree	
No university degree or other	19.2%
Bachelor's degree	33.7%
Master's Doctorate degree	47.1%
Age Distribution	
18 - 23 years old	26%
23 - 27 years old	43.3%
27 - 32 years old	15.4%
Over 32 years old	15.3%

Regarding academic degree, 14.4% of participants had no university degree, 47.1% held a master's or doctorate degree, 33.7% had a bachelor's degree, and 4.8% selected the "other" option. For data analysis purposes, the "other" and "no university degree" categories were combined.

The age distribution of the participants was as follows: 26% were between 18 and 23 years old, 43.3% were between 23 and 27 years old, 15.4% were between 27 and 32 years old, and 15.3% were over 32 years old.

4.1. Independence of Variables

4.1.1. Independence of Gender and Favorite Social Network

The independence of gender and favorite social network was examined using the chi-square test. The results of this analysis are presented in following Table 2:

According to the Table 3, the P-value is equal to 0.831, which is greater than 0.05. Therefore, we fail to reject the null hypothesis, indicating that there is not enough evidence to suggest a significant relationship between the variables of gender and favorite social network. Hence, we can conclude that the two variables are independent of each other.

Table 2. Frequency (independence of gender and favorite social network).

		Social Media		Total
		Instagram	Twitter	
Gender	Female	34	23	57
	Male	29	18	47
	Total	63	41	104

Table 3. Chi-Square (independence of gender and favorite social network).

	value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	0.045	1	0.831		
Continuity correction	0.000	1	0.991		
Likelihood Ratio	0.045	1	0.831		
Fisher's Exact Test				0.843	0.496
N of Valid Cases	104				

4.1.2. Independence of Age and Favorite Social Network

The following Table 4 is based on the chi-square test for the two variables of age and favorite social network:

According to the Table 5, the P-value is equal to 0.04, which is less than the significance level of 0.05. Therefore, we reject the null hypothesis and conclude that there is a significant relationship between age and the favorite social network. In other words, they are dependent on each other.

Table 4. Frequency (independence of age and favorite social network).

		Social Media		Total
		Instagram	Twitter	
Age	18 - 23	15	10	25
	23 - 27	34	12	46
	27 - 32	6	10	16
	Over 32	8	9	17
	Total	63	41	104

Table 5. Chi-Square (independence of age and favorite social network).

	Value	df	Asymptotic Significance (2-Sided)
Pearson Chi-Square	8.292	3	0.040
Likelihood Ratio	8.352	3	0.039
N of Valid Cases	104		

4.1.3. Independence of Academic Degree and Favorite Social Network

The following Table 6 is based on the chi-square test for the two variables of academic degree and favorite social network:

According to the Table 7, the P-value is equal to 0.651, which is greater than the significance level of 0.05. Therefore, we fail to reject the null hypothesis and conclude that there is not enough evidence to suggest a significant relationship between the variables of academic degree and favorite social network. Hence, we can conclude that the two variables are independent of each other.

Table 6. Frequency (independence of academic degree and favorite social network).

		Social Media		Total
		Instagram	Twitter	
Academic Degree	Master's degree and Ph.D.	28	21	49
	No university degree	11	8	19
	Bachelor's degree	24	12	36
	total	63	41	104

Table 7. Chi-Square (independence of academic degree and favorite social network).

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	0.858	2	0.651
Likelihood Ratio	0.867	2	0.648
N of Valid Cases	104		

4.1.4. Independence of Academic Degree and Gender

The following Table 8 is based on the chi-square test for the two variables of academic degree and gender:

According to the Table 9, the P-value is equal to 0.139, which is greater than the significance level of 0.05. Therefore, we fail to reject the null hypothesis and conclude that there is not enough evidence to suggest a significant relationship between the variables of gender and academic degree. Hence, we can conclude that the two variables are independent of each other.

Table 8. Frequency (independence of academic degree and gender).

		Academic Degree			total
		Master's degree and Ph.D.	No University degree	Bachelor's degree	
Gender	Female	22	13	22	57
	Male	27	6	14	47
	Total	49	19	36	104

Table 9. Chi-Square (independence of academic degree and gender).

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	3.942	2	0.139
Likelihood Ratio	3.981	2	0.137
N of Valid Cases	104		

4.1.5. Independence of Academic Degree and Age

The following Table 10 is based on the chi-square test for the two variables of academic degree and age:

According to the Table 11, the P-value is insignificant, which is much smaller than 0.05. Therefore, we reject the null hypothesis and conclude that there is a significant relationship between the variables of academic degree and age.

Table 10. Frequency (independence of academic degree and age).

		Academic DEGREE			`Total
		Master's degree and ph.d	No University education	Bachelor's degree	
Age	18 - 23	1	18	6	25
	23 - 27	27	0	19	46
	27 - 32	10	1	5	16
	Over 32	11	0	6	17
	Total	49	19	36	104

Table 11. Chi-Square (independence of academic degree and age).

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	66.837	6	0.000
Likelihood Ratio	68.321	6	0.000
N of Valid Cases	104		

4.1.6. Independence of Gender and Age

The following Table 12 is based on the chi-square test for the two variables of gender and age:

According to the Table 13, the p-value is 0.247, which is greater than 0.05. Therefore, we fail to reject the null hypothesis, suggesting that there is no significant association between gender and age variables. Hence, we can conclude that these two variables, gender and age, are independent of each other.

Table 12. Frequency (independence of gender and age).

		Age				Total
		18 - 23	23 - 27	27 - 32	Over 32	
Gender	Woman	17	21	8	11	57
	Man	8	25	8	6	47
	Total	25	46	16	17	104

Table 13. Chi-Square (independence of gender and age).

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	4.135	3	0.247
Likelihood Ratio	4.192	3	0.241
N of Valid Cases	104		

4.1.7. Summary of the Results

According to the Table 14, it is evident that the age variable is dependent on both academic degree and the social network of interest. Therefore, these three variables cannot be combined to construct a single tree. For this purpose, a separate tree should be created for each section involving the variables of gender,

Table 14. Summary of the results.

	Gender	Social Network	Age	Academic degree
Gender	-	Independent	Independent	Independent
Social Network		-	Independent	Independent
Age			-	Independent
Academic degree				-

academic degree, and social network of interest. In addition, another tree can be constructed specifically for the gender and age variables, as they are found to be independent of each other.

4.2. Decision Tree

In this section, a decision tree is created on the basis of the demographic responses of individuals to the WTB and SOI questionnaires, the independence of the demographic variables, and their responses to the Leybman test. The decision tree visually represents the relationships and patterns between these variables. The leaves of the tree are labeled with the terms "High" and "Low". A leaf labeled "High" indicates that the corresponding branch leads to a value higher than the target average, whereas a leaf labeled "Low" indicates a value lower than the target average. The thickness of the strip inside each leaf represents the abundance level. A thicker strip signifies higher abundance, whereas a thinner strip indicates lower abundance.

4.2.1. WTB Variable Decision Tree

According to the structure of the decision tree, the Figure 2, academic degree can be a significant factor in classifying people based on their willingness to buy green products. The tree begins by dividing the data based on the academic degree variable. However, it appears that gender alone and preferred social network are not influential factors for classifying people in terms of their willingness to buy green products. Conversely, the decision tree suggests that gender, along with age, can be influential factors for classifying people based on their willingness to buy green products as it is showed in Figure 3.

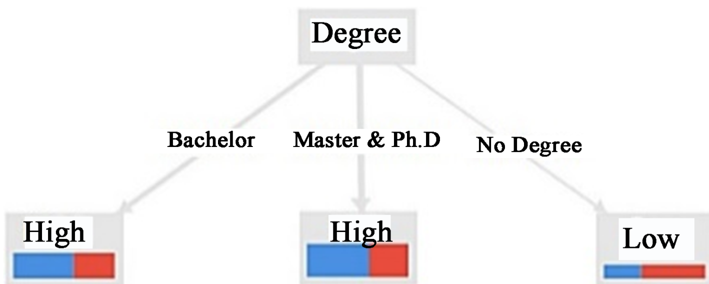

Figure 2. Academic degree based on WTB variable decision tree.

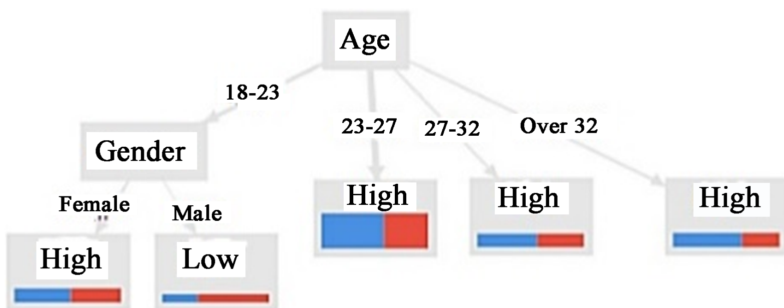

Figure 3. Age and Gender based on WTB variable decision tree.

4.2.2. SOI Variable Decision Tree

According to the findings, it is concluded in the Figure 4 that gender, academic degree, and social network of interest, together can be factors for classifying people in terms of the degree of influence from others in buying green products. As can be seen in Figure 5, the software uses the gender variable as the root of the tree, Therefore, the decision considers the age variable. Hence, gender in age is one of the factors influencing the influence of others in buying green products.

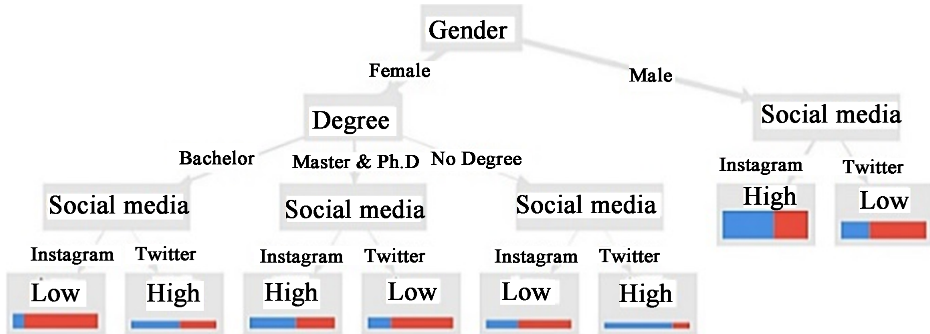

Figure 4. Gender, academic degree, and social media based on SOI variable decision tree.

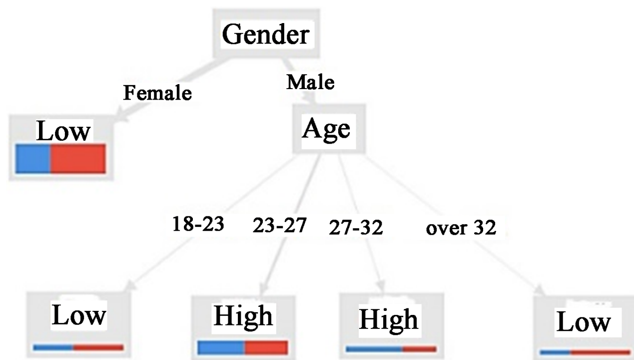

Figure 5. Gender and age based on SOI variable decision tree.

4.2.3. Active Viral Marketing (AVM) Variable Decision Tree

In Figure 6, it is evident that the final score of active viral marketing, which combines the two previously mentioned components, begins to branch based on the academic degree variable. Furthermore, in the subsequent stage in Figure 7, the software considers the variables of age and gender for further branching.

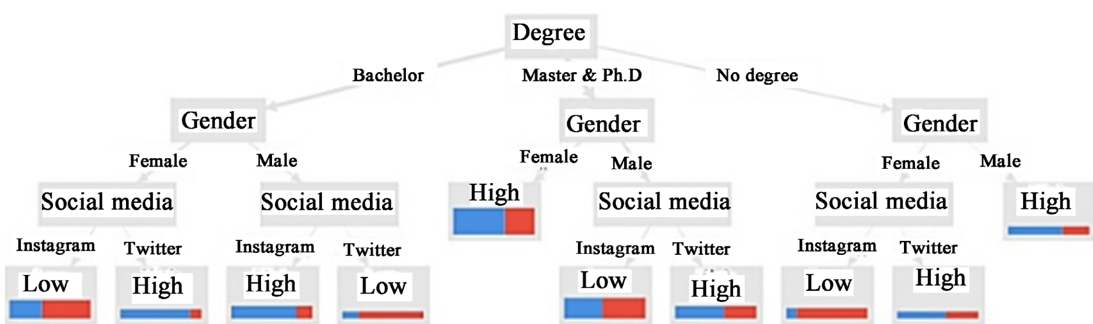

Figure 6. Academic degree, gender, and social media based on AVM variable decision tree.

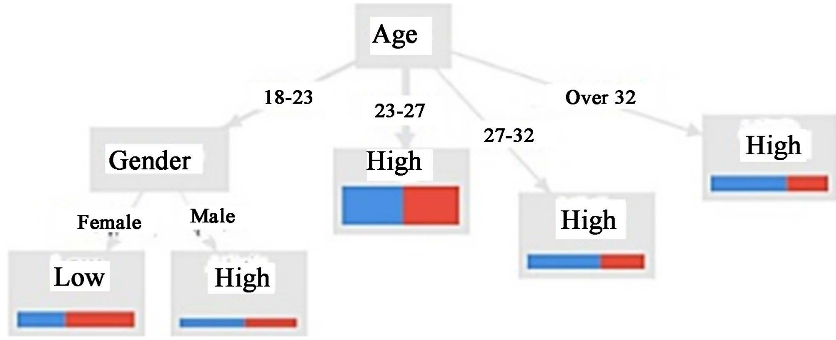

Figure 7. Age and gender based on AVM variable decision tree.

4.2.4. Leybman Test Decision Tree

The shape of the decision tree of the Leybman test, which is used to assess people's desire to interact and communicate with others, shows that the software has identified the gender variable as an influencing variable on this test and used it as the root of the decision tree (Figure 8). In the next step, the gender and social network variables of interest were selected as branches (Figure 9).

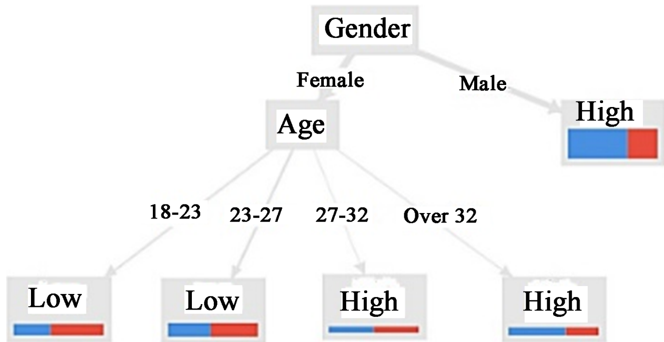

Figure 8. Gender and Age based on Leybman test decision tree.

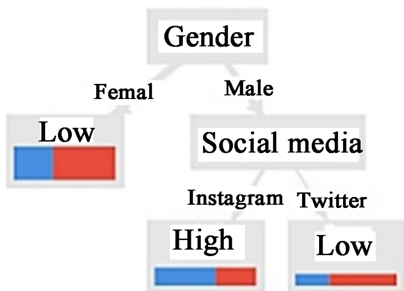

Figure 9. Gender and Social media based on Leybman test decision tree.

4.3. Combination of the Leybman Test and the Active Viral Marketing (AVM) Algorithm

Independence Test of the Active Viral Marketing Score and Leybman Test Score

Based on the Table 15 provided, the obtained P-value is less than 0.05, indicating a statistically significant relationship between the variable of active viral marketing score and Leybman test scores. Therefore, according to the Table 16, we can conclude that these two variables are dependent on each other rather than independent.

Table 15. Frequency (independence test of the active viral marketing score and Leybman test score).

		Leybman Test Score		Total
		High	Low	
Active Viral Marketing Score	High	38	18	56
	Low	22	26	48
	Total	60	44	104

Table 16. Chi-Square (independence test of the active viral marketing score and Leybman test score).

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	5.136	1	0.023	0.029	0.019
Continuity Correction	4.274	1	0.039		
Likelihood Ratio	5.165	1	0.023	0.029	0.019
Fisher's Exact Test				0.029	0.019
N of Valid Cases	104				

5. Discussion

The findings of this study provide valuable insights into the relationship between demographic variables and social network preferences, as well as their impact on various aspects such as willingness to buy green products, influence from others in buying green products, active viral marketing, and the Leybman test.

First, the analysis revealed no significant relationship between gender and a favorite social network. This finding is consistent with previous studies that reported no significant gender differences in social network preferences (Mari et al., 2023). However, this study only examined the relationship between gender and two specific social networks, Instagram and Twitter. Further research could explore the relationship between gender and other social networks to provide a more comprehensive understanding.

In contrast, the study found a significant relationship between age and the favorite social network. Specifically, the analysis showed that age and favorite social network are dependent on each other. This finding aligns with previous research that highlighted the influence of age on social network preferences.

Younger individuals tend to gravitate toward platforms such as Instagram, whereas older individuals may prefer different social networks. This information is valuable for marketers and advertisers targeting specific age groups (Adilova, 2023).

Regarding academic degree, the analysis did not find a significant relationship between academic degree and a favorite social network. This suggests that academic degree level does not play a significant role in determining social network preferences. This finding is consistent with some previous studies that have also reported no significant association between academic degree and social network preferences (Laor, 2022). However, it is important to acknowledge that academic degree can still influence other aspects of online behavior and engagement, such as information seeking and digital literacy (Jalali & Bouyer, 2019).

The decision tree analysis provided further insights into the factors influencing willingness to buy green products, the degree of influence from others in buying green products, active viral marketing, and the Leybman test. The decision trees revealed that academic degree can be a significant factor in classifying people based on their willingness to buy green products. This finding is consistent with previous research that highlighted the role of academic degree in shaping environmental attitudes and behaviors (Hong et al., 2023). Additionally, the decision trees indicated that gender and age can also be influential factors in classifying individuals based on their willingness to buy green products. This suggests that gender and age may influence environmental consciousness and consumer behavior.

Furthermore, the analysis demonstrated a significant relationship between the scores of active viral marketing and the Leybman test. This finding suggests that individuals who are more inclined to engage in active viral marketing are also more likely to desire interaction and communication with others. This aligns with previous research that highlighted the relationship between social influence and online behavior (Wang et al., 2015; Liu et al., 2018).

It is important to acknowledge the limitations of this study. First, the sample size was relatively small, consisting of 104 participants. A larger sample size would enhance the generalizability of the findings. In addition, the study focused on only two social networks: Instagram and Twitter. Including a wider range of social networks would provide a more comprehensive understanding of social network preferences. Furthermore, the study relied on self-reported data, which may be subject to biases and inaccuracies.

In terms of implications, the findings of this study can be valuable for marketers and advertisers in understanding the demographic factors that influence social network preferences and consumer behavior. By tailoring their strategies to specific age groups and considering the influence of academic degree, marketers can effectively target their desired audience. In addition, the findings highlight the importance of social influence and viral marketing in shaping consumer behavior, particularly in the context of green products.

Further research would be beneficial to explore the relationship between gender and social network preferences across a wider range of social networks. In addition, investigating the role of other demographic variables, such as income and occupation, in shaping social network preferences and consumer behavior would provide a more comprehensive understanding. Furthermore, conducting longitudinal studies to examine changes in social network preferences and consumer behavior over time would provide valuable insights into the dynamics of online behavior.

Overall, this study provides valuable insights into the relationship between demographic variables and social network preferences and their impact on various aspects of consumer behavior. The findings highlight the influence of age on social network preferences, the role of academic degree in shaping environmental attitudes, and the relationship between active viral marketing and the desire for interaction with others. These findings have implications for marketers and advertisers and suggest avenues for further research to deepen our understanding of online behavior and consumer preferences.

6. Conclusion

The conclusion of this document highlights the importance of actively promoting environmentally friendly products through viral marketing as a means of mitigating the negative impact of human actions on the environment. This study emphasizes the effectiveness of using demographic data obtained through contemporary social media methods for targeted marketing. This suggests that smaller organizations can benefit from data mining techniques, sophisticated graph calculations, and viral marketing algorithms to implement successful viral marketing strategies.

The key findings of this study indicate that academic degree and age are the primary drivers of success in active viral marketing. Gender and social media interests also play a significant role in this marketing approach. The Leybman test, combined with demographic variables, provides valuable insights into individuals' desires and behaviors, helping to classify social networking behaviors and decisions. The decision tree analysis revealed that academic degree influences individual motivation to purchase green products, whereas age surpasses gender in determining the likelihood of purchasing environmentally friendly products.

This study also highlights the importance of social networks in spreading promotional messages and the desire for social interaction and communication. This suggests that organizations can leverage active viral marketing to harness consumers' desires for eco-friendly products and influence their social networks. By combining the Leybman test and active viral marketing, the efficiency of marketing strategies can be greatly enhanced.

In conclusion, this study emphasizes the significance of active viral marketing as a powerful tool for promoting green products and engaging green-minded consumers. This study provides valuable insights into the ideal candidate for successful viral marketing and highlights the role of academic degree, age, gender, and social media interests in this marketing approach. The findings suggest that organizations should prioritize green marketing and explore the use of viral marketing tactics to effectively target and engage environmentally conscious consumers. Further research can focus on building comprehensive models and conducting surveys to assess individuals' motivation and willingness to engage with and spread the message. Overall, this study offers innovative methods and promising insights for the development and implementation of effective marketing strategies in the context of environmental sustainability.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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