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Social Media Influencers: Customer Attitudes and Impact on Purchase Behaviour

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Abstract: Social media marketing has become a crucial component of contemporary business strategies, significantly influencing brand visibility, customer engagement, and sales growth. The aim of this study is to investigate and determine the key factors guiding customer attitudes towards social media influencers, and, on that basis, to explore their effects on purchase intentions regarding advertised products or services. A total of 376 filled-in questionnaires from an online survey were analysed. The main characteristics of digital influencers' behaviour that affect consumer perceptions have been systematized and categorized through a combination of both traditional and advanced data analysis methods. Structural equation modelling (SEM), machine learning and multi-criteria decision-making (MCDM) methods were selected to uncover the hidden dependencies between variables from the perspective of social media users. The developed models elucidate the underlying relationships that shape the acceptance mechanism of influencers' messages. The obtained results provide specific recommendations for stakeholders across the social media marketing value chain. Marketers can make informed decisions and optimize influencer marketing strategies to enhance user experience and increase conversion rates. Working collaboratively, marketers and influencers can create impactful and successful marketing campaigns that resonate with the target audience and drive meaningful results. Customers benefit from more tailored and engaging influencer content that aligns with their interests and preferences, fostering a stronger connection with brands and potentially affecting their purchase decisions. As the perception of customer satisfaction is an individual and evolving process, stakeholders should organize regular evaluations of influencer marketing data and explore the possibilities to ensure the continuous improvement of this e-marketing channel.

Keywords: social media marketing; influencer marketing; customer satisfaction; behaviour intention; purchase intention; structural equation modelling; PLS-SEM; machine learning; MCDM

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1. Introduction

Social media influencers, also referred to as digital influencers, online influencers or internet influencers, came into prominence at the beginning of the 21st century, during the transition from the early Web 1.0 environment to the collaborative Web 2.0 era. Initially, companies only sought celebrities to stimulate successful product sales. Today, online influencers are key figures who attract and captivate audiences with their specialized knowledge or intriguing lifestyle, making them valuable assets for brands when establishing a strong online presence [1]. Influencer marketing is a form of internet advertising that builds brand loyalty based on the reputation, recommendations, and popularity of a given celebrity or well-known personality [2]. The rise of social media has turned influencer marketing into a preferred tool for brand awareness and sales promotions.

The COVID-19 health crisis has been one of the catalysts for technological advancements in marketing strategies. As people spent more time online due to lockdowns and restrictions, online influencers became key marketing instruments for brands to connect with their target audiences. The pandemic led to a greater proliferation of social media influencers as sources of information and product recommendations [3,4].

According to Statista's analysis [5], the global influencer marketing market was valued at USD 21.1 billion as of 2023, representing a substantial increase of 224.6% from the pre-pandemic level of USD 6.5 billion in 2019 and a 28.7% increase from the previous year's level of USD 16.4 billion in 2022. As per the Influencer Marketing Hub report [6], the influencer marketing industry is projected to reach around 24 billion by the end of 2024. In this report, nearly a quarter of the surveyed participants planned to allocate over 40% of their total marketing budget to influencer campaigns. This growth underscores the importance of influencer marketing as a communication channel for reaching and engaging audiences.

However, there is no unified framework for researching the features of this digital marketing tool. Studying the factors that affect user perceptions regarding influencers and predicting their impact on the customer decision-making process is a complex issue for the following three main reasons:

1. The heightened ambiguity and complexity of the current economic landscape rapidly alter customer needs, preferences, and purchasing habits. For instance, during economic recessions, consumers may prioritize only essential goods and services, indicating a shift in preferences and a reduced willingness to spend [7].
2. The advancements in modern technologies, including virtual reality, live-streaming, and mobile applications, have the potential to improve the methods and platforms used by digital influencers as advertising tools [8].
3. The array of methods for customer satisfaction research has been broadened with the introduction of big data, sentiment analysis, multi-criteria decision-making methods, fuzzy logic, neural networks, and their combinations [9,10]. These new analytical capabilities facilitate the discovery of new dependencies in influencer marketing data.

These challenges prompt us to investigate user perceptions regarding internet influencers using classical statistical methods and modern techniques such as structural equation modelling (SEM) and machine learning (ML), as well as multi-criteria decision-making (MCDM) methods.

The objective of this study is to develop and verify a new structural and discriminative ranking model to ascertain the impact of digital influencers on customer perceptions regarding their convenience, interactivity, attractiveness, expertise and trustworthiness. The models should also incorporate various socio-economic and demographic factors such as monthly household income per capita, communication behaviour, age, place of residence, education level, etc.

The main tasks of the study are as follows:

- Create a conceptual framework that enables the systematic analysis of consumer data and the uncovering of hidden relationships in customer attitudes towards digital influencers.
- Arrange and collect a customer dataset on customer experiences and preferences in social media marketing (including socio-economic indicators, respondents' perceptions regarding digital influencers, and specific issues).
- Identify the key factors affecting the buying intentions generated by online influencers and propose methods for their impact determination, based on a review of previous research.
- Develop and validate mathematical models based on factors recognized in the previous task and compare them to those sourced from similar studies that were conducted previously.

This study examines customer attitudes towards internet influencers by categorizing perception factors into three main groups. The derived weights of these factors from the structural cause-and-effect model can be utilized in multi-criteria assessment systems to compare digital influencers' campaigns. The primary contribution of this paper lies in the creation of new models for evaluating, comparing, and predicting customer attitudes towards online influencers, products or services, utilizing both traditional and intelligent methods for data analysis.

The remainder of this paper is structured as follows: Section 2 outlines the main characteristics of social media influencers. Section 3 introduces related research on customer attitudes towards digital influencers. Section 4 discusses the structure and content of the questionnaire and proposes measurement indicators, based on those utilized in previous research. Section 5 analyses the collected dataset, establishes mathematical models, and then verifies them. The obtained results are then compared to those from existing studies. The paper concludes in the final section, where future research directions are outlined.

2. State-of-the-Art Review of Influencer Marketing

Digital influencers are individuals who have established their expertise or authority in a specific industry or niche, often with many engaged followers on social media platforms. They leverage their status to promote brands, products or services to their audience, creating authentic and relatable content. For businesses, the benefits of collaboration with social media influencers include reaching a targeted audience, building brand awareness, and driving engagement and conversions through the influencers' trusted recommendations [11,12].

However, managers of brick-and-mortar stores, physical retail outlets, conventional media companies and other traditional marketing stakeholders are often unfamiliar with the capabilities of this innovative marketing channel for brand positioning. This knowledge deficiency results in a lack of alignment with the evolving demands of customers, who seek valuable information, entertainment, or inspiration in the virtual space. Moreover, it could lead to unnecessary marketing expenditure without a corresponding return on investment [12].

2.1. Key Features and Taxonomy of Social Media Influencers

Starting in the 2000s, online influencers have revolutionized traditional marketing with technological innovations. Influencers are adept at creating high-quality and attractive content, including photos, blog posts and videos, which resonates with their audience. Through active engagement such as responding to comments, clicks, likes, and shares, influencers create a sense of community. Some of the recent trends [13,14] are as follows:

- Growing reliance on video materials: Influencers focus on creating high-quality videos, especially short video forms on platforms like TikTok and Instagram. These formats are appealing, even to users with short attention spans. Additionally, the platforms' algorithms promote viral content and amplify the popularity of these videos.
- Social commerce: The integration of e-commerce and social media platforms is growing rapidly. Users can discover, shop, and purchase products directly from social media platforms like Facebook Marketplace, Pinterest and TikTok, which offer e-commerce features.
- Diversification of platforms: Influencers expand their content presence across various platforms to reach different audiences. This approach ensures that influencers connect with their followers, regardless of their preferred online spaces.
- Virtual influencers and AI: The rise of AI-generated influencers is an emerging trend because these influencers offer an innovative approach to brand collaborations. However, this format can lead to a lack of sincerity in interactions with the audience and decrease the level of users' trust and engagement with virtual personalities.
- Data-driven influencer marketing: Intensified competition among social media influencers necessitates the implementation of data-driven influencer marketing. Brands now rely on data analytics and AI to pinpoint the most suitable influencers for their campaigns. These data-driven decisions not only lead to measurable results but also yield more effective partnerships.

Each internet influencer has unique characteristics that attract diverse audiences. Based on their attributes, content creators can be categorized in various ways according to different criteria.

Content Focus: Influencers often specialize in specific niches or content types [15], such as business and entrepreneurship, technologies and gaming, health and fitness, fashion and beauty, travel, and adventure, among many others.

Form of Internet Marketing: Influencers can be classified based on the forms of internet marketing they use, such as content creation, social media presence, video production, blogging, affiliate marketing, etc. [16]. These categories help brands identify influencers who align with their marketing goals and target audience. From content creators to brand ambassadors, each category offers its own approach to reaching and engaging with audiences online.

Platform: Influencers can be grouped based on the social media platforms on which they are active. While Instagram influencers focus on visual content such as photos and short videos, YouTube influencers create long-form video content like tutorials and vlogs. TikTok influencers utilize short, creative, and entertaining videos, while X (formerly Twitter) influencers share real-time updates and involve users in conversations [11].

Reach: This criterion refers to the size of influencer audiences, typically measured in terms of the number of followers or subscribers. Influencers can be classified based on their reach into four main categories: mega, macro, micro and nano influencers with millions, hundreds of thousands, tens of thousands and several thousand followers, respectively [11]. The efficiency of influencers is not solely dependent on their audience size, but also on many other features such as their engagement rates.

Audience Demographics: Influencers can also be grouped based on the demographics of their audience: age, gender, location, and income level of their followers. Some influencers appeal to specific demographics, while others have a more diverse audience [17].

The above taxonomy can be used by businesses and marketers to identify the influencers that align best with their marketing objectives and target audience. Each influencer category offers unique advantages and can be leveraged based on the specific campaign goals and budget.

2.2. Assessing Online Influencers

When evaluating and comparing Internet influencers, various assessment tools can be employed to measure their quality and efficiency. These tools can be categorized into three main areas: marketing metrics, compound indices, and theoretical models. These benchmarks work together to enhance our understanding and improvement of the adoption and spread of influencer marketing.

2.2.1. Marketing Metrics

Marketing metrics assess the efficiency of online influencers, in a similar way to that when traditional internet marketing instruments (such as website content, display advertising, email, affiliate, and video marketing) are evaluated. A variety of metrics for assessing influencer impact and user engagement are provided by social media platforms via embedded analytical tools, including Meta Business Suite Insights, TikTok Analytics, and X Analytics.

The most widely used metrics are detailed below.

Engagement rates: These factors measure how actively the audience interacts with the influencer's content. The engagement rate can be determined by the number of likes, comments, shares, reactions, and other forms of interaction that a post receives in relation to the total number of followers or views [18]. A high engagement rate indicates that the audience is attentive and responsive to the influencer's posts.

Follower growth: This measure indicates the rate at which the influencer's follower count is increasing over time. It reflects the influencer's ability to attract new followers and expand their audience, which can be a sign of increasing influence and popularity [19].

Website traffic from social media: This influencer marketing metric tracks the relationship between influencers' activities in social media and brand website visits, demonstrating the strength of influencer campaigns in encouraging potential customers to explore a brand further by visiting its websites [20].

Key performance indicators (KPIs) for influencer marketing [21] depend on the goals of the campaign and the specific metrics that are important to the brand. Click-through rate (CTR) and conversion rate are essential KPIs for measuring the quality and efficiency of influencer content, while brand sentiment provides indicators for brand perception among the influencer's audience. Content quality, as a subjective assessment, encompasses visual appeal, creativity, and storytelling within the influencer's content. Brand mentions show the frequency and context of references by the influencer, indicating their relationship with and endorsement of a brand [22]. Share of voice (SOV) calculates the percentage of mentions or conversations that an influencer has compared to others in the same industry or niche [23].

The metrics employed for influencer classification (Section 2.1) can also be applied to assess the efficiency of online influencers.

2.2.2. Compound Indices

Each index considers a combination from various metrics such as reach, engagement, relevance, and authority [24]. Lee and Eastin developed and validated a multi-dimensional measure of perceived authenticity of social media influencers (PASMIs), consisting of sincerity, truthful endorsements, visibility, expertise, and uniqueness [25]. Zhuang et al. proposed a complex measurement approach to determine both the users' topic-level influence and the users' global-level influence [26]. There are numerous pre-defined influencer indices available, with the Klout score being one of the earliest examples. This rates an influencer's social media impact on a scale from 1 to 100, considering factors like followers, engagement, and activity. Its successors aim to provide a more comprehensive view of an influencer's efficiency in the digital space. These indices can be accessed through social media analytics platforms or mobile apps. For example, each social media platform has its own algorithm to rank posts in users' feeds, but there are differences in how these algorithms work to determine a post's popularity.

Despite the oversight of organizations like the Interactive Advertising Bureau (IAB) in online marketing, there are currently no specific standards for assessing influencers. While there are no direct guidelines pertaining to social media marketing practices, some existing standards can be indirectly applied to influencer marketing. For instance, ISO 20671 provides recommendations for the evaluation and measurement of brand value, which can be relevant when assessing the impact of influencer marketing on a brand [27].

2.2.3. Theoretical Models

These models utilize different theories to measure the effects of digital influencers' behaviour on their audience. Rogers's diffusion of innovations theory (1962) model focuses on how new ideas, products, and behaviours are spread through society. It assesses how influencers can act as early adopters and opinion-leaders, impacting the diffusion process [28,29]. Social cognitive theory (1963) emphasizes how individuals learn from observing others, including influencers. It explores how influencers' behaviours and messages can influence the beliefs, attitudes, and actions of their followers [30,31]. The elaboration likelihood model (1986) looks at how individuals process persuasive messages. It categorizes influencers' content into the central route (careful consideration of arguments) and peripheral route (quick, emotional reactions), predicting how followers will respond [32,33]. The belief-attitude-behaviour theory [34] suggests that beliefs affect intentions through their effect on attitudes towards the behaviour. The theory of reasoned action (1975) later extends the belief-attitude-behaviour model by adding the concept of subjective norms to explain behavioural intentions. The theory of planned behaviour (1988) builds upon the theory of reasoned action, incorporating the component of perceived behavioural control to enhance predictions of individual behaviour [35,36]. Ohanian's source credibility model (1990) evaluates the perceived credibility of the influencer. It considers factors such as expertise, trustworthiness, and attractiveness, which affect the way in which followers interpret and accept influencer messages [37,38].

These theoretical models provide conceptual frameworks for understanding how influencers impact their audiences; furthermore, they can guide research into the efficiency of digital marketing campaigns.

3. Related Work

3.1. Customer Attitudes towards the Role of Influencer Recommendations on Purchase Intention and Its Measurement

In the last fifteen years, there has been growing interest among both e-commerce practitioners and academic researchers in the impact of digital influencers on purchase intention. In social media marketing, purchase intention refers to the likelihood of a consumer purchasing a product or service after exposure to marketing efforts on social media platforms. It reflects the consumer's readiness to buy being influenced by social media content like advertisements, sponsored posts, reviews, or influencer recommendations. This factor is vital for businesses as it helps predict potential sales and the effectiveness of their social media marketing initiatives.

Lim et al. explored the effectiveness of social media influencers, focusing on the influence of four factors—source credibility, source attractiveness, product match-up, and meaning transfer [39]. The authors employed the partial least squares (PLS)-SEM technique to test a model with a sample dataset of 200 respondents in Malaysia. The study revealed that three hypotheses were supported, except for that related to source credibility. The hypothesis on the mediating effect of consumer attitude on purchase intention was also supported.

To determine the attitude of customers towards digital influencers' activities, Xiao et al. utilized a heuristic-systematic model to investigate how information credibility affects customers' evaluations of influencers' posts on YouTube [40]. The authors examined the relationships between nine key constructs—expertise, trustworthiness, likeability, homophily, social advocacy, interactivity, argument quality, information involvement and knowledge. A two-step, structural equation modelling data analysis approach was preferred to explore the correlation between variables. The study reported that trustworthiness, social influence, argument quality, and information involvement are factors with a positive impact on consumer-perceived information credibility on YouTube. The analytic results also reveal a strong and positive correlation between perceived information credibility, brand attitude, and video attitude.

Chekima et al. clarified the relevance of three factors that affect attitudes towards digital influencers in the Malaysian cosmetic industry [41]. This research examined the impact of social media influencer credibility (attractiveness, trustworthiness, and expertise) on advertising effectiveness, specifically focusing on attitudes towards the product and advertisement, as well as purchase intention. The goal was to determine the suitability of hiring a social media influencer to advertise cosmetic products in the local Malaysian market, as compared to using a celebrity. The study discovered that source credibility has a significant positive impact on consumer attitudes. Therefore, using influencer marketing, cosmetic product marketers can develop effective ads to communicate with their customers.

Yuan and Lou proposed and verified the determinants of the relationship between social media influencers and their followers, as well as their effects on the followers' interests in the products advertised by influencers [42]. The conceptual model includes eight key constructs—attractiveness, expertise, trustworthiness, similarity, distributive, procedural, interpersonal, and informational fairness. The obtained results showed that the impact of four input constructs on the output variables are statistically significant: followers' perceptions of the attractiveness of influencers, their similarity to influencers, and procedural and interpersonal fairness.

Pham et al. developed a research model to determine the impact of influencers on Vietnamese Generation Z (Gen Z) in the internet environment [43]. A conceptual model was developed based on a 24-question survey. The input variables were categorized into the following second-order constructs: argument quality, perceived usefulness, and social influence, each comprising attractiveness, expertise, and trustworthiness. The analysis of the obtained results confirmed the research hypotheses that attitudes towards social media influencers in the Vietnamese market directly depend on the given constructs.

Ata et al. investigated the most significant factors influencing consumer purchase intention following social media advertising in Turkey [44]. Their study found that attractiveness, expertise, and trustworthiness positively influenced buying behaviour. However, they observed that the impact of attitude towards social media advertising on purchase intention was statistically insignificant.

Ebrahimi et al. studied how social network marketing affected the consumer purchase behaviour of Hungarian users in Facebook Marketplace [45]. The results of this study indicate that five constructs (entertainment, customization, interaction, WoM, and trend) have positive and significant effects on customer buying decisions. Furthermore, the authors used clustering algorithms to cluster consumers. Using the obtained cluster profiles, marketing managers can develop targeted strategies tailored to the preferences and characteristics of each cluster.

Niloy et al. analysed four influencing factors (source credibility, source attractiveness, product match-up, and source familiarity) and two output constructs (attitude towards influencers and purchase intention) using multiple linear regression (MLR) [46]. The results revealed that attitudes towards influencers were positively correlated and significantly influenced by source attractiveness, product match-up, and source familiarity. However, source credibility was found to be an insignificant factor impacting attitudes towards influencers.

Ooi et al. investigated the impact of mobile convenience, interactivity, and influencer credibility on the attitude towards a social media influencer and the attitude towards an advertised product or service, as well as how these outcomes lead to actual buying decisions. The results indicate that interactivity plays negative direct and indirect roles on both user attitudes. Furthermore, attitude towards a product or service is a factor that mediates the direct effect of attitude towards the social media influencer on purchase intention [47].

Al-Sous et al. surveyed the impact of social media influencers on consumer behaviour by examining two factors affecting the influence purchase intentions of Jordanian Facebook users—information quality and trustworthiness [48]. The results confirmed the significant impact of both factors on attitude towards a brand, which, in turn, determines customer purchase intentions.

Coutinho et al. studied the factors that influence consumer attitude (brand equity) and purchase intention by conducting an empirical study in the context of Portuguese social media marketing [49]. The authors developed a conceptual model that includes four key constructs—attractiveness, expertise, trustworthiness and brand equity—and tested the model using an SEM with survey data. The analysis indicated that both constructs (attractiveness and brand equity) have a significant positive impact on consumer purchase intention, and they are positively interrelated.

3.2. Comparison of Existing Models of User Attitudes towards Social Media Influencers

The studies outlined in the preceding subsection rely on factors originating from seminal works in the field of source credibility theory, including credibility and attractiveness [50] and attractiveness, expertise, and trustworthiness [51]. The majority of studies have employed PLS-SEM, while two models have been built using other techniques—machine learning k-means clustering [45] and multiple linear regression [46]. The key characteristics of models illustrating the factors affecting the user perception of social media marketing are outlined in Table 1.

Table 1. Comparison between models of customer attitudes and purchase intentions in social media marketing.

Reference	Utilized Algorithm	Evaluation Metrics (Number)	Statistically Significant Factors (Number)	R^2
Lim et al. (2017) [39]	PLS-SEM	Source credibility, Source attractiveness, Product match-up, Meaning transfer (4) → Customer attitude → Purchase intention	Source attractiveness, Product match-up, Meaning transfer (3)	0.490; 0.708
Xiao et al. (2018) [40]	PLS-SEM	Expertise, Trustworthiness, Likeability, Homophily, Social advocacy, Interactivity, Argument quality, Involvement, Knowledge (9) → Brand attitude	Trustworthiness, Social advocacy, Argument quality, Involvement (4)	–; N/A
Chekima et al. (2020) [41]	PLS-SEM	Attractiveness, Expertise, Trustworthiness (3) → Ad attitude, Product attitude, Purchase intention	Attractiveness, Expertise, Trustworthiness (3)	0.514, 0.558; 0.671
Yuan et al. (2020) [42]	PLS-SEM	Attractiveness, Expertise, Trustworthiness, Similarity, Distributive, Procedural, Interpersonal and Informational fairness (8) → Parasocial relationship → Purchase interest	Expertise, Similarity, Procedural fairness, Interpersonal fairness (4)	0.740; 0.530
Pham et al. (2021) [43]	PLS-SEM	Attractiveness, Expertise, Trustworthiness → Argument quality, Perceived usefulness and Social influence (9) → Attitude → Purchasing behaviour	Attractiveness, Expertise, Trustworthiness (9)	0.571; 0.501
Ata et al. (2022) [44]	PLS-SEM	Attractiveness, Expertise, Trustworthiness (3) → Attitude → Purchase intention	Attractiveness, Expertise, Trustworthiness (3)	0.765; N/A
Ebrahimi et al. (2022) [45]	PLS-SEM, k-means	Entertainment, Customization, Interaction, Word of mouth, Trend (5) → Customer purchase behaviour	Entertainment, Customization, Interaction, Word of mouth, Trend (5)	N/A; 0.841
Niloy et al. (2023) [46]	MLR	Source credibility, Source attractiveness, Product match-up, Source familiarity (4) → Attitude → Purchase intention	Source attractiveness, Product match-up, Source familiarity (3)	0.527; 0.653
Ooi et al. (2023) [45]	PLS-SEM	Convenience, Interactivity, Source credibility (Attractiveness, Expertise, Trustworthiness) (5) → Attitude towards SMI, Attitude towards the product or service → Purchase intention	Convenience, Interactivity, Attractiveness, Expertise, Trustworthiness (5)	0.745, 0.776; 0.484

Table 1. *Cont.*

Reference	Utilized Algorithm	Evaluation Metrics (Number)	Statistically Significant Factors (Number)	R^2
Al-Sous et al. (2023) [48]	PLS-SEM	Information quality, Trustworthiness (2) → Attitude towards a brand → Influence purchase intentions	Information quality, Trustworthiness (2)	–; –
Coutinho et al. (2023) [49]	PLS-SEM	Attractiveness, Expertise, Trustworthiness → Brand equity (4) → Customer purchase intention	Attractiveness, Brand equity (2)	0.623; 0.811

Note: In the last column, R^2 represents the determination coefficient. The symbol ";" separates the coefficient value(s) for "Attitude(s)" from that of "Purchase intention". "N/A" indicates "Not Applicable", while the symbol "–" signifies missing data.

The distribution of constructs in the above-mentioned models is as follows: purchase intention—9/11; attractiveness (likeability and similarity)—9/11; trustworthiness—8/11; attitude towards the advertisement, brand, product, or service, including product interest—7/11; expertise—7/11, attitude towards influencers (parasocial relationship)—6/11; convenience (perceived usefulness and product match-up)—4/11; interactivity (interaction)—3/11; argument quality—2/11, etc. The effectiveness of the models proposed in the literature varied from 49.0% [39] to 84.1% [45], with the number of latent variables ranging from 2 to 9. The number of statistically significant factors fluctuated in the same interval.

Despite considerable research on the factors affecting customer satisfaction in internet influencer marketing, widely accepted metrics for evaluating this online marketing tool are still lacking. Additionally, current research on the impact dimensions of social media influencers in the European Union electronic market context is limited and does not fully consider dynamic changes in consumer preferences and behaviour. Therefore, identifying new approaches and conducting empirical investigations in this field can help fill in these gaps and offer valuable insights for both businesses and marketing agencies.

3.3. Main Factors Affecting Consumer Attitudes towards Social Media Influencers and Their Impact on Buying Decisions

The source credibility theory, interactivity theory, and the theory of planned behaviour can be adapted and applied to comprehend the adoption and acceptance of influencers, particularly in the context of digital marketing and social media platforms. Based on the literature review, the primary factors determining user attitudes towards social media influencers can be represented in a theoretical model with three main input constructs: convenience, interactivity, and source credibility. Source credibility is a second-order construct encompassing influencer attractiveness, expertise, and trustworthiness. This combination offers the advantage of integrating both internal factors (convenience and interactivity) and external factors (source credibility) related to social media platforms, thereby enhancing consumer purchase intention. The following section provides a detailed overview of the factors in our proposed model.

3.3.1. Convenience

The concept of convenience originates from the ease of use and perceived usefulness of technology in the technology acceptance model (TAM) [52] and the unified theory of acceptance and use of technology (UTAUT) [53]. It encompasses factors such as mobile access, user-centric interfaces, fast loading times, and intuitive navigation. Convenience allows users to connect quickly and effortlessly with others, consume content, and react to posts and updates. It also enables businesses and influencers to reach their target audience, as users are more likely to engage with content that is easily accessible and user-friendly [54,55].

3.3.2. Interactivity

The notion of interactivity in communication research, especially in relation to emerging digital media technologies, has been investigated by numerous scholars [56,57]. Interactivity in social media is defined as the degree to which users can actively engage with content and with other users on the platform [58]. Unlike push marketing in the past, interactive social media marketing creates a real-time dialogue between the business and its customers. Advertising has become a dynamic process that follows customers rather than leading them [58]. Interactivity enhances user engagement and supports community-building on social media platforms. Influencers leverage the feedback provided, such as consumers' impressions and preferences, to tailor and direct their advertising endeavours more effectively [59].

3.3.3. Source Credibility

The source credibility theory [60] postulates that the credibility of endorsers could influence the beliefs, attitudes, and behaviours of receivers towards the endorsed objects. Kelman's source characteristics [50] identify three features of successful marketing communication sources: credibility, attractiveness, and power.

The dimensionality and dimensions of source credibility varied among the researchers, depending on the study. Expertise and trustworthiness are two predictors of source credibility, according to a study by Hovland et al. [61]. Some later studies have employed attractiveness and trustworthiness to determine the reliability of source expertise [37]. All three dimensions were important in purchase intentions and affected involvement with the advertisement message equally [51].

Brands can employ source credibility theory by carefully selecting influencers who are perceived as credible by their audience. They focus on influencers who demonstrate expertise, trustworthiness, and attractiveness, as these qualities enhance the effectiveness of brand messages. Influencers employ credibility theory principles to establish and uphold their credibility, emphasizing consistency in brand values, transparency in sponsored content, and engagement with followers to foster trust and loyalty.

(a) Attractiveness

The source attractiveness model, introduced by McGuire [62], supplements the source credibility theory by highlighting the impact of source attractiveness on message effectiveness. This model posits that source attractiveness, which includes familiarity, likeability, and similarity, can influence how a message is perceived. It is commonly combined with the source credibility model to evaluate the effects of endorsements and testimonials on consumer attitudes and purchase intentions. Source attractiveness, along with trustworthiness and expertise, contribute to the overall credibility of marketing communications.

Attractiveness includes factors such as the influencer's personality, appearance, content style, and overall reputation. An attractive influencer can captivate their audience's attention, increase engagement, and build a loyal following [41,63].

(b) Expertise

The expertise of online influencers refers to their knowledge and authority in a specific niche or industry. An influencer with expertise is seen as knowledgeable, credible, and trustworthy by his/her audience. He/she is considered an expert in his/her field, which enhances his/her ability to influence the opinions, behaviours, and purchasing decisions of their followers [39,64].

(c) Trustworthiness

The trustworthiness of social media influencers refers to the perceived reliability, honesty, and credibility of the influencer according to their audience. An influencer who is considered trustworthy is more likely to have loyal followers who believe in his/her recommendations and opinions. Trustworthiness is crucial for building and maintaining a strong relationship with followers, which, in turn, influences the followers' purchase decisions and brand preferences [65,66].

The output constructs of the proposed model of social media influencer effects on users are attitudes towards influencers, brands, and/or products/services, which together contribute to forming a purchase intention.

3.3.4. Attitude towards Social Media Influencers

The concept of attitude towards social media influencers refers to the general feelings, beliefs, and evaluations that individuals hold about influencers on social media platforms. This factor can be analysed using the belief-attitude-behaviour model, aiding in understanding how beliefs about influencers translate into attitudes and subsequent actions [67]. This factor can significantly impact a consumer's behaviour, influencing his/her engagement with influencer content, willingness to follow recommendations, and overall brand perception.

3.3.5. Attitude towards Brand, Product, or Service

This concept is central to theoretical models like the theory of reasoned action and the theory of planned behaviour, which explain how attitudes towards products and services impact consumer behaviours and intentions. Attitude towards a brand refers to an individual's preferences, feelings, beliefs, and evaluations regarding a particular brand [68]. These three attitudes reflect their overall perception and liking of the brand, product, or service, which can influence consumer buying behaviour and purchase intentions. Positive attitudes typically lead to a higher likelihood of purchasing or recommending the brand, product, or service, while negative attitudes can deter consumers from engaging with or purchasing the brand, product, or service.

3.3.6. Purchase Intention

Purchase intention refers to a consumer's predisposition or plan to buy a particular product or service in the future. As a key concept in consumer behaviour research, it indicates the likelihood of a purchase, based on various factors such as attitudes, perceptions, and external influences [69]. The term is defined by individual consumers based on their needs, preferences, attitudes, perceptions, and various other factors. It is not defined by a single entity but, rather, emerges from the complex dependencies between personal, social, cultural, and economic influences on an individual's decision-making process [70,71].

Based on the synthesis and comparison of existing models for customer attitudes towards internet influencers (Table 1) and an analysis of the factors related to social media platforms, the research hypotheses in this study are formulated as follows [47] (Figure 1):

H_1: *There is a significant impact of convenience on customer attitude towards social media influencers.*

H_2: *There is a significant impact of interactivity on customer attitude towards social media influencers.*

H_3: *There is a significant impact of influencer credibility on customer attitude towards social media influencers.*

H_4: *There is a significant impact of influencer credibility on customer attitude towards products or services.*

H_5: *There is a significant impact of attitude towards social media influencers on customer attitude towards products or services.*

H_6: *There is a significant impact of customer attitude towards social media influencers on purchase intention.*

H_7: *There is a significant impact of customer attitude towards products or services on purchase intention.*

H_8: *Customer demographic characteristics have statistically significant mediating effects on customer attitudes or on purchase intentions.*

Note: The demographic characteristics include gender, age, educational level and residence.

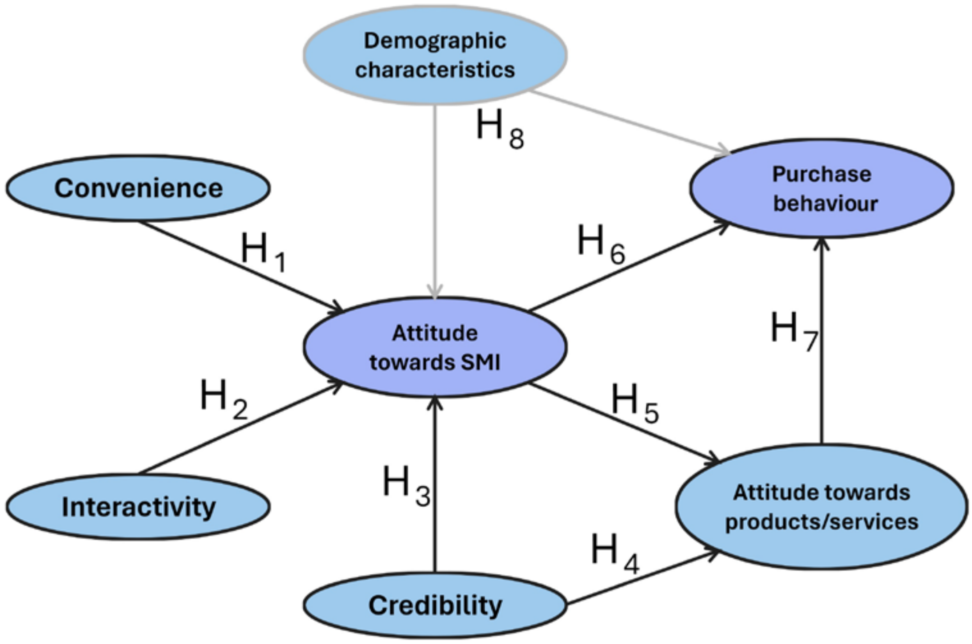

Figure 1. Structural diagram of the research hypotheses.

The formulated hypotheses can reveal the significance of highlighted factors on diverse aspects of consumer attitudes towards social media influencers. In the following section, this study employs an integrated approach to assess how these factors influence customer purchase behaviour in relation to attitudes towards influencers, brands, and products.

4. Research Methodology

Our research methodology aims to uncover and describe customer perceptions of digital influencers, with a focus on forecasting future changes. To achieve this goal, we will collect primary data and employ a variety of analytical techniques. These techniques include descriptive statistics and predictive machine learning methods, along with a multi-criteria decision-making approach. Additionally, we will conduct sentiment analysis on user opinions to identify common issues faced during interactions with social media influencers. These results will offer valuable insights for marketing managers to address customer concerns and refine their marketing strategies accordingly.

4.1. Questionnaire Design and Data Collection

The survey method was chosen as a primary research tool due to its ability to collect a large volume of data and analyse it to gain insights into customer preferences and behaviour regarding social media influencers. Online surveys were particularly favoured for their wide reach, convenience, cost-effectiveness, ease of design, and relatively quick processing. A questionnaire was designed that was based on previous research on customer perceptions of interactions with digital influencers [54,72–74], following the format proposed by Ooi et al. [47]. The questionnaire comprises five main sections: introduction, demographics, experience with social media influencers, attitudes towards them and towards products or services, and purchasing intentions.

Indicators for Question #10 (convenience) and Question #11 (interactivity) were adapted from the research of Wu and France et al., respectively [54,74]. Both the convenience and interactivity factors consist of five indicators each. The items for Question #12 (attractiveness), Question #13 (expertise), and Question #14 (trustworthiness) were sourced from the work of Munnukka et al. [73]. Question #15 and Question #16, which measure attitude towards influencers and attitude towards products or services, respectively, were obtained from the work of Silvera and Austad [72]. The last five factors (attractiveness, expertise, trustworthiness, attitude towards influencers, and attitude towards products or services) consist of four indicators each. Two indicators for Question #17 (purchase intention) for respondents' expenditures due to social media influencer advertising were adapted from the work of Cheung et al. [75]. To incorporate the participants' opinions, suggestions, and their favourite influencers, the last two questions (Question #19 and Question #20) were included based on recommendations from marketing experts [76]. The research details and questionnaire link were disseminated through partner organizations via classic web and social media communications.

4.2. Questionnaire Measurements and Scales

Approximately 35% of the survey questionnaire (7 out of 20) is composed of "multiple choice grid" questions that implement a five-point Likert scale, ranging from "strongly disagree" to "strongly agree". A further 40% of the questionnaire (8 out of 20) comprises "multiple choice" questions. Three questions require open-ended text responses to be entered into text fields marked as "short answer" or "paragraph" in Google Forms. Finally, two questions are formulated using a five-point linear scale.

4.3. Data Analysis Methods

The data analysis methods for the investigation of user attitudes towards social media influencers can be divided into three main groups: statistical methods, machine learning methods, and multi-criteria decision-making methods.

The first group comprises methods that measure object properties, then we summarize and visualize the main characteristics of multi-dimensional data. The analysis utilizes techniques such as tests for normality, *t*-tests, an analysis of variance (ANOVA), the chi-squared test, and regression analysis. Partial least squares structural equation modelling (PLS-SEM), as a modern statistical method, also belongs to this category because it is particularly suited for complex models with latent variables and smaller sample sizes [77].

Machine learning methods such as cluster analysis, predictive modelling, and sentiment analysis are employed to uncover hidden relationships between variables. Cluster analysis group similar observations, while sentiment analysis extracts and analyses subjective information from text opinions. By utilizing ML methods, researchers can uncover hidden patterns and relationships between variables that may not be apparent using traditional statistical methods. Unlike statistical methods, ML algorithms do not focus on testing theoretical models or finding causal relationships. Instead, they are data-driven and aim to predict future outcomes based on past data patterns.

MCDM methods provide a systematic approach to decision-making in influencer marketing, considering multiple criteria simultaneously to make informed and data-driven choices. MCDM techniques can be applied for marketing campaign evaluation, content optimization, influencer selection, and other similar problems requiring the ranking of alternatives.

While classical and modern statistical methods like SEM are suited for hypothesis testing and for understanding complex theoretical models, machine learning methods are more data-driven and are focused on extracting insights from large datasets, primarily for tasks such as prediction, segmentation, and sentiment analysis. In contrast, MCDM methods provide a comprehensive approach to analysing consumer attitudes towards social media influencers, offering a more nuanced understanding of consumer preferences and behaviour.

The benefits of integrating various data analysis methods for social media influencer research include: obtaining an overall view, improving accuracy, enhancing segmentation, optimizing campaigns, validating data, monitoring in real time, and making strategic decisions.

5. Data Analysis

The proposed methodology (Section 4) has been applied to address the research tasks.

Customers' Data Collection

We distributed the online survey link via our institution's websites, email, and social media platforms. The survey was aimed at Bulgarian online customers, and participation was voluntary. Utilizing Google Forms, the survey comprises 20 questions designed to gauge customer perceptions of the variables in this study [76]. Data on customer attitudes towards social media influencers were collected from 8 January 2024 to 14 March 2024. A total of 376 respondents completed the questionnaire. Duplicate checking was conducted, and no identical values were found in the dataset rows. However, the model construct data (Question #10 to Question #18) revealed one duplicate dataset row (#337 duplicates #233). Since the dataset does not contain completely identical records, all observations will be included in the analysis.

Figure 2 visualizes the degree of similarity among respondents' answers, with closer distances indicating smaller differences. The degree of similarity is depicted by different colours, ranging from full coincidence (0—light blue colour) to maximum difference (25—darker blue colour). To visualize the dissimilarity matrix, we utilized the fviz_dist() function from the factoextra R package.

Data storage

The questionnaire and respondents' answers are available online [76].

Data encoding

The coding rules and coded data are accessible online [76]. Among the 20 questions, responses to 17 questions have been coded. Additionally, the three open-text answers (municipality, opinions, and a list of followed influencers) have undergone further processing.

Data preprocessing

Preprocessing was conducted, and the dataset underwent examination to ensure accuracy and consistency.

Statistical analysis

To clarify the profile of the participants in the survey, a classical statistical analysis (percentage distribution of responses, descriptive statistics, and correlation analysis) has been performed.

Main Characteristics of Respondents in the Sample

Table 2 presents the demographics of the survey participants. Most respondents were female, making up 74% of the total participants (Question #1). More than two-thirds (72%) of the respondents were under the age of 30 (Question #2). The sample was evenly split between individuals with at least a university degree, accounting for 50.2%, and those with higher education (50.8% of the participants) (Question #6). Additionally, the survey primarily targeted urban areas, with 94.6% of the respondents residing in such locations (Question #3).

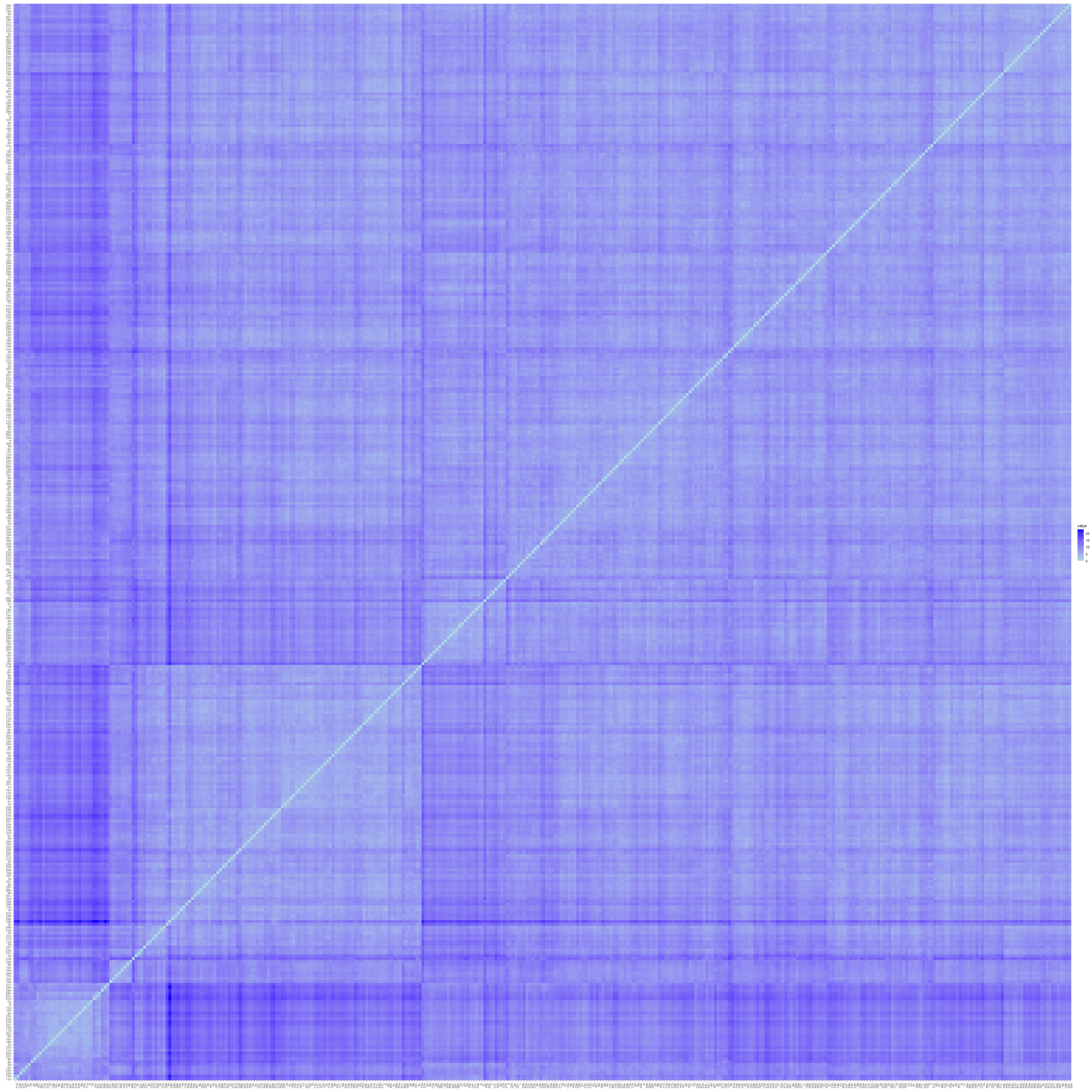

Figure 2. The ordered dissimilarity matrix of the respondents' answers.

In terms of geographic distribution, most respondents were from the Plovdiv municipality, comprising 52% of the total survey participants. Additionally, the Asenovgrad municipality represented 5% of the total respondents, while the Pazardzhik municipality accounted for 4% of the respondents (Question #4). Geographically, the survey was primarily conducted in the south-central region, covering 82.2% of the participants, followed by the southwestern region (3.7%).

Table 2. Customer profiles in the sample (n = 376).

Variables of the Sample		No. of Consumers	Percentage (%)
1. Gender	Male	99	26.3
	Female	277	73.7
2. Age	Under 20	88	23.4
	Between 21 and 30	183	48.7
	Between 31 and 40	42	11.2
	Between 41 and 50	50	13.3
	Over 50	13	3.5
3. Place of residence	City	241	64.1
	Town	127	33.8
	Village	8	2.1
4. Municipality		-	-
5. Monthly income per household member	Less than BGN 1320	141	37.5
	More than BGN 1320	235	62.5
6. Education	High school	191	50.8
	Bachelor	119	31.6
	Master	61	16.2
	PhD	5	1.3
7. Experience with social media	Less than 3 years	31	8.2
	3 to 5 years	47	12.5
	More than 5 years	298	79.3
8. Frequency of use of social media	Less than once a week	3	0.8
	Once or twice a week	1	0.3
	Several times a week	10	2.7
	Once or twice a day	40	10.6
	Several times a day	241	64.1
	Several times an hour	81	21.5
9. Number of influencers that you follow on social media	Less than 10	184	48.9
	10 to 20	99	26.3
	20 to 30	44	11.7
	More than 30	49	13.0

Ninety-six per cent of the participants indicated that they visited social media sites daily (Question #8), aligning with findings from Statista regarding daily social media usage [78]. Furthermore, more than half of the respondents (51.1%) stated that they followed more than 10 influencers (Question #9). This percentage reflects a significant increase compared to the adoption of digital influencers in developed countries such as the UK, where only 15% reported following 10 or more influencers [79] in 2023. One possible explanation for this contrast is that 59.9% of respondents in our sample belonged to Generation Z and Millennial classifications.

Feature selection

To visualize the spectrum of attitudes towards digital influencers, we employed hierarchical clustering with heat maps, as depicted in Figure 3 for observations and Figure 3 for attributes. The colour gradient in the heat maps corresponds to standardized values, ranging from light blue (minimum value approximately −2.60) to blue (maximum value approximately 3.90). The hierarchical structure shown atop Figure 2 illustrates the grouping of respondents based on their similar attitudes. Similarly, the dendrogram in Figure 4 (right) illustrates the similarities between variables. These heat maps reveal clusters of data points with similar characteristics, without any notable anomalies or irregularities. The Heat Map widget in Orange 3.22.0 software was utilized to generate these visualizations.

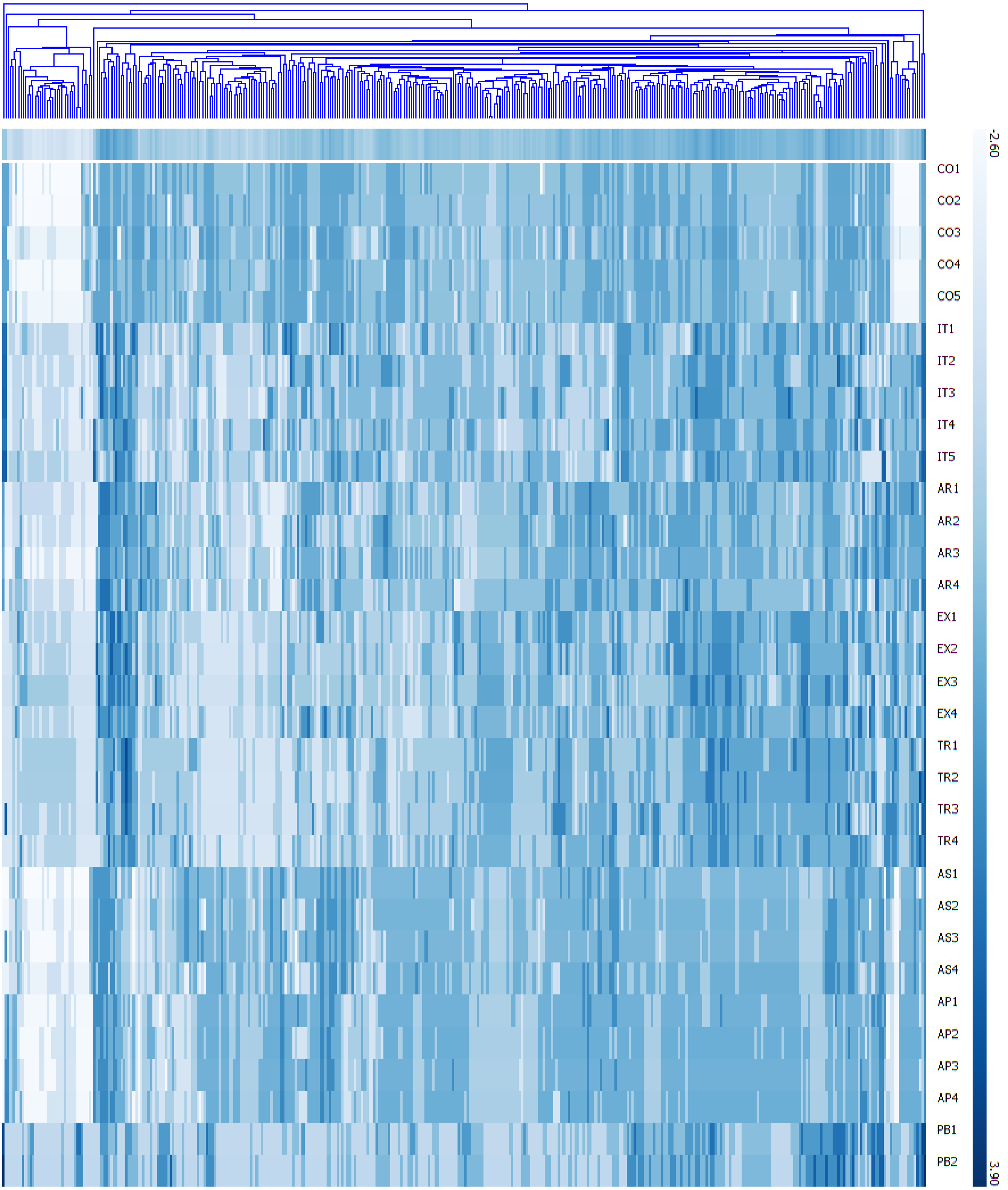

Figure 3. Hierarchical group heat map, shown by respondents.

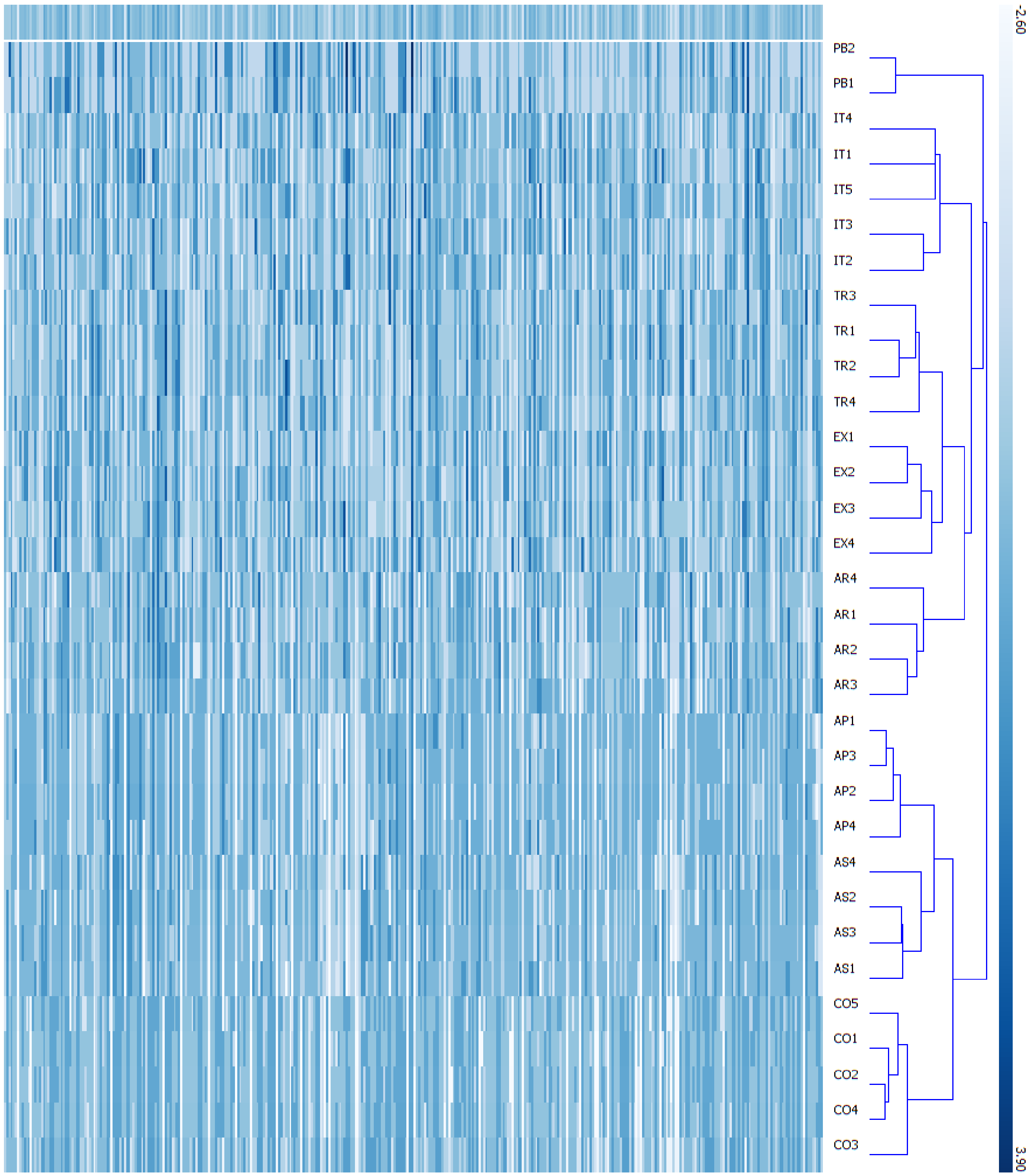

Figure 4. Hierarchical group heat map, shown by indicators.

5.1. Clustering

To identify groups of customers with similar characteristics and variables that had a comparable effect on consumer attitudes, we employed the *k*-means method for cluster analysis. The number of clusters was determined using the elbow and silhouette methods, and the results revealed that the optimal number of clusters was two. The two clusters consisted of 334 and 42 respondents, respectively. Figure 5 shows that when $k = 2$, there is no overlap between the clusters. This means that the *k*-means method offers a feasible solution to the problem of identifying clusters of customers with similar attitudes towards internet influencers.

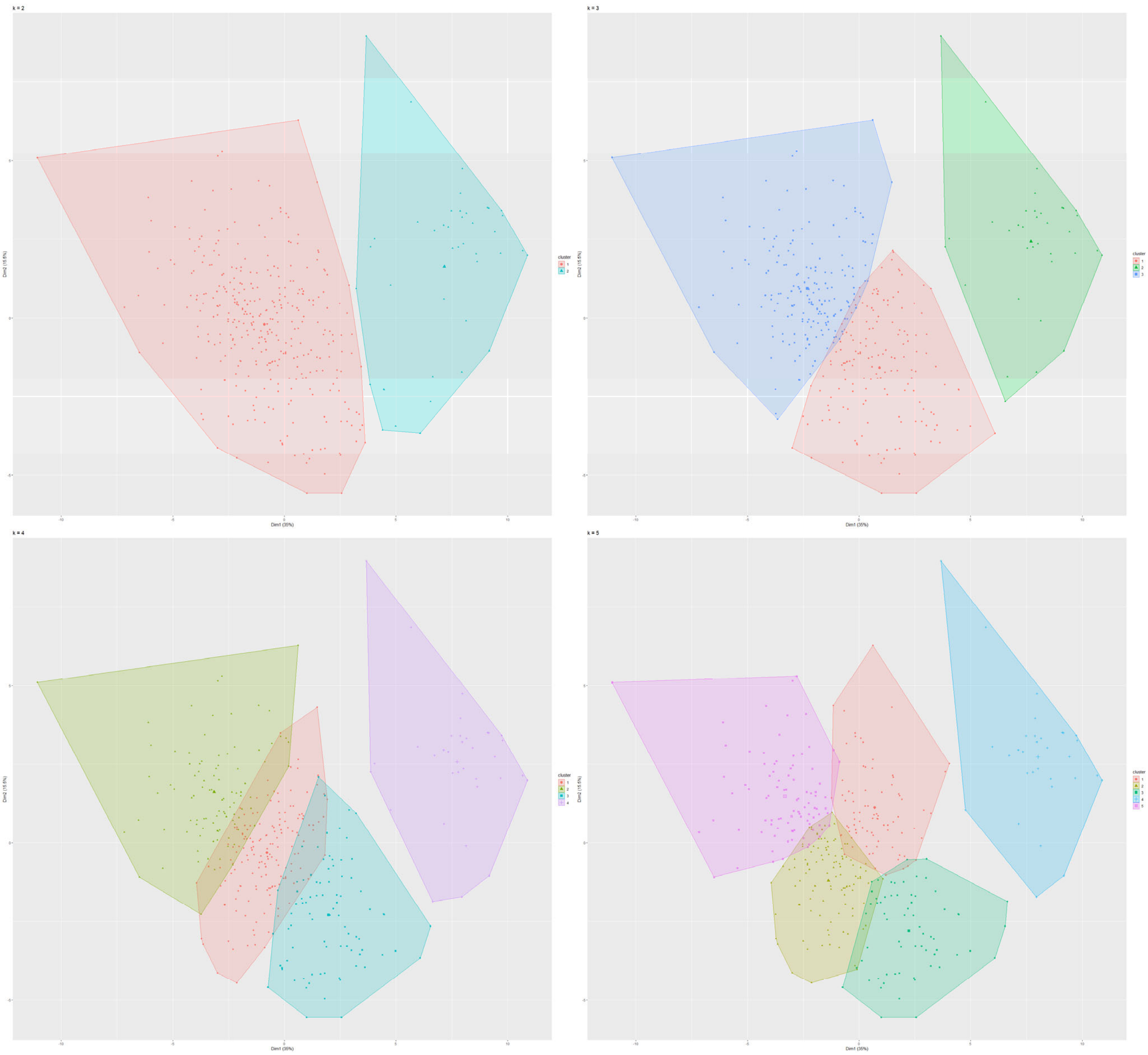

Figure 5. Customer clusters created by *k*-means (*k* = 2, 3, 4, 5), using 32 input indicators.

The first cluster (Cluster #1) comprised 334 "satisfied" customers, demonstrating more positive perceptions of social media influencers. They exhibited higher ratings for influencer characteristics (Question #10—Question #14), attitudes towards influencers and products or services (Question #15 and Question #16), and purchase intentions (Question #17 and Question #18) (Table 3). Among the indicators, convenience (Question #10), attractiveness (Question #12), and expertise (Question #13) exerted the strongest influence on overall satisfaction. In contrast, the second cluster reflected some dissatisfaction with digital influencer relationships, with trustworthiness (Question #14) and interaction (Question #12) being the most significant factors contributing to the negative attitude of this group of users. Table 3 illustrates the average values of the indicators for both clusters, along with the differences between these estimates.

Table 3. Average values by cluster and the absolute differences between clusters, shown by indicators.

	CO1	CO2	CO3	CO4	CO5	IT1	IT2	IT3	IT4
Cluster #1	4.222	4.263	3.931	4.186	4.195	2.829	2.850	2.868	3.015
Cluster #2	2.000	1.976	1.976	1.929	1.714	1.762	1.738	1.714	1.738
Difference	2.222	2.287	1.955	2.257	2.480	1.067	1.112	1.154	1.277
	IT5	**AR1**	**AR2**	**AR3**	**AR4**	**EX1**	**EX2**	**EX3**	**EX4**
Cluster #1	2.590	3.084	3.210	3.575	3.027	2.668	2.545	2.249	2.695
Cluster #2	1.643	1.810	1.786	1.762	1.976	1.667	1.595	1.762	1.595
Difference	0.947	1.274	1.424	1.813	1.051	1.001	0.950	0.487	1.099
	TR1	**TR2**	**TR3**	**TR4**	**AS1**	**AS2**	**AS3**	**AS4**	**AP1**
Cluster #1	2.302	2.356	2.458	2.605	3.880	3.760	3.808	3.539	3.671
Cluster #2	1.714	1.714	1.595	1.690	1.810	1.667	1.762	1.714	1.738
Difference	0.588	0.642	0.863	0.914	2.071	2.094	2.046	1.825	1.933
	AP2	**AP3**	**AP4**	**PB1**	**PB2**				
Cluster #1	3.572	3.665	3.560	1.880	1.737				
Cluster #2	1.762	1.833	1.905	1.548	1.476				
Difference	1.810	1.831	1.655	0.333	0.260				

5.2. Sentiment Analysis

The open-ended question regarding respondents' opinions about social media influencers (Question #19) elicited 146 text responses. Following preprocessing and filtering, 140 responses remained, reflecting user perceptions about influencers. Sentiment analysis of these responses yielded the following scores: 61 positive (average value 0.751), 21 neutral (average value 0.524), and 47 negative (after excluding 11 opinions with a score of less than 0.010; average value 0.181). Overall, respondents generally supported digital influencers as a convenient source of information, although negative opinions often centred around concerns regarding the influencers' expertise regarding promoted products and their trustworthiness in endorsing certain product categories. Neutral opinions acknowledged the benefits of digital influencer usage but highlighted behavioural weaknesses. The Azure Machine Learning add-in in MS Excel was utilized for the sentiment analysis.

The final open-ended question concerning preferred social media platforms and influencers (Question #20) garnered responses from 257 participants (after preprocessing). The resulting rankings for the top 5 social media platforms closely resembled those found in a recent research report [80], with a Spearman correlation coefficient of 0.742. Similarly, the rankings for the top 5 influencers, based on their number of followers, also presented a strong similarity, with a Spearman correlation coefficient of 0.883. These findings underscore the consistency of preferences among respondents and align closely with broader online marketing trends.

5.3. SEM Model of Customer Attitude and Purchase Intention towards Digital Influencers

Based on a review of previous research (Section 3), there is a lack of consensus regarding the definition of inputs and outputs for evaluating consumer perceptions and attitudes towards social media influencers. To address this issue, we iteratively utilized the PLS-SEM method via SmartPLS software version 3.2.9 [81]. Additionally, we adhered to the standard five-step procedure for PLS-SEM model creation.

Step 1. Formulate hypotheses about the input and output variables and their relationships.

Eight research hypotheses were formulated at the end of Section 3.

Step 2. Identify indicators for latent variables.

Indicators of latent variables were available in the survey questionnaire: 8 constructs with 32 indicator variables [76]. The measurement model consists of 22 input indicators: CO1, CO2, CO3, CO4, and CO5, from the variable convenience (CO); IT1, IT2, IT3, IT4, and IT5, from the variable interactivity (IT); AR1, AR2, AR3, and AR4, from the variable interactivity (IT); EX1, EX2, EX3, and EX4, from the variable experience (EX); TR1, TR2, TR3, and TR4 from the variable trustworthiness (TR); and ten output indicators: AS1, AS2, AS3, and AS4 from the output variable of attitude towards social media influencers (AS), AP1, AP2, AP3, and AP4 from the output variable of attitude towards products or services (AP), and PB1 and PB2 from the output variable of purchase intention (PB), as represented in Figure 6.

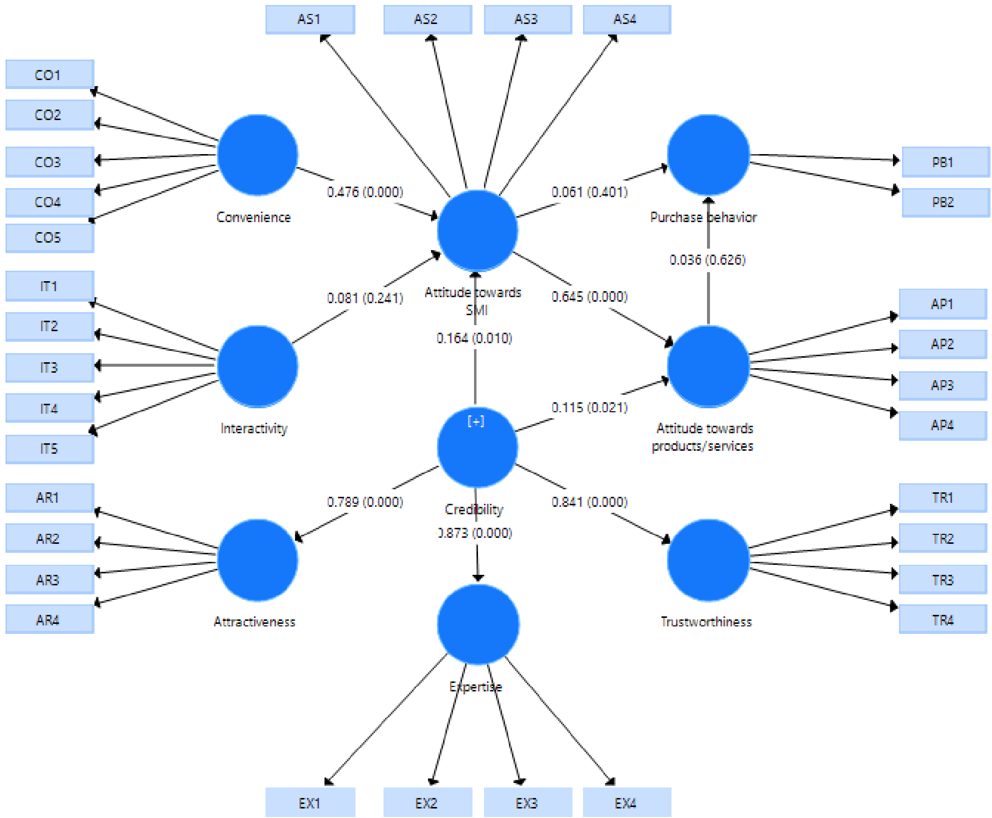

Figure 6. Measurement model with nine latent variables, along with their path coefficients and *p*-values.

Step 3. Conduct numerical modelling and evaluate the quality of the model.

Utilize the PLS algorithm to derive model parameters.

Step 4. Assess the suitability of the model. If it fits the data, proceed to Step 5. Otherwise, return to Step 3 to refine the model.

According to the assessment of path coefficients, our second-order model does not fit the data well. This is due to the *p*-values of interactivity and purchase intention as a function of attitude towards social media influencers and attitude towards products or services, which are 0.241, 0.401, and 0.626, respectively, and are outside the acceptable limit (Figure 6). As a result, the process needs us to return to Step 3 and change the model settings by removing some model factors. As the *p*-values of the path coefficients for the new model are acceptable, the model examination continues to establish the construct's reliability and validity (Step 4).

5.3.1. Validity and Reliability

The first phase of the validity assessment process entails examining both the measurement and structural models. The measurement model aims to establish the construct validity and reliability, involving assessment of construct reliability, indicator reliability, convergent validity, and discriminant validity. Conversely, the structural model focuses on verifying the significance of the proposed relationships.

5.3.2. Factor Loadings

Factor loadings indicate the extent to which each item in the correlation matrix correlates with the designated principal component. Higher absolute values signify a stronger correlation between the item and the underlying factor, as detailed by Pett et al. [82]. In this study, all items exhibit factor loadings exceeding the recommended threshold of 0.5, as suggested by Hair et al. [83]. The achieved measurement model and the corresponding factor loadings are illustrated in Figure 7 and Table 4.

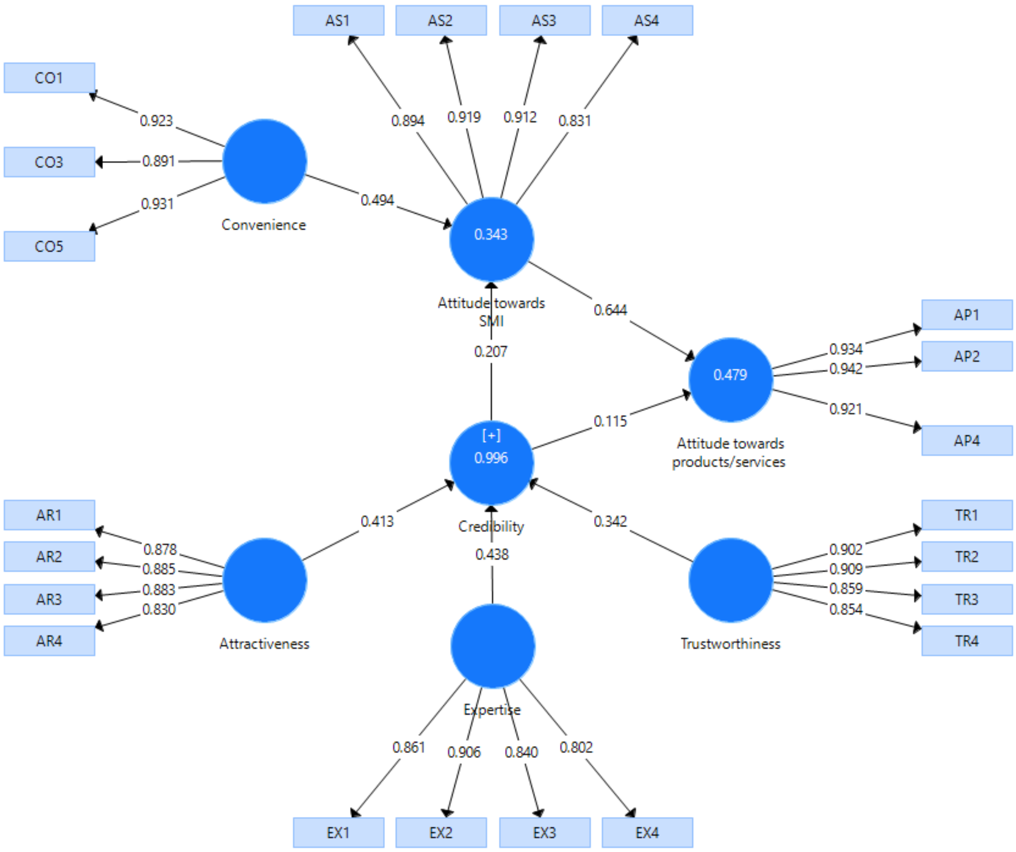

Figure 7. SEM procedure validity result—path coefficients and coefficients of determination.

Table 4. Factor loadings for indicators.

Indicator Variable	Factor Loading	Indicator Variable	Factor Loading	Indicator Variable	Factor Loading
CO1	0.923	EX2	0.906	AS2	0.919
CO3	0.891	EX3	0.840	AS3	0.912
CO5	0.931	EX4	0.802	AS4	0.831
AR1	0.878	TR1	0.902	AP1	0.934
AR2	0.885	TR2	0.909	AP2	0.942
AR3	0.883	TR3	0.859	AP4	0.921
AR4	0.830	TR4	0.854		
EX1	0.861	AS1	0.894		

5.3.3. Indicator Multicollinearity

To assess the multicollinearity among indicators, the study utilizes the Variance Inflation Factor (VIF) statistic. VIF value below five indicates acceptable multicollinearity. Table 5 presents the VIF values for each indicator, all of which fall below the recommended threshold [84].

Table 5. Construct reliability (DG rho and CR), convergent validity (AVE) and multicollinearity (VIF).

Factor	DG rho	CR	AVE	VIF
Convenience	0.909 *	0.939 *	0.837 *	1.080 *
Credibility	0.911 *	0.924 *	0.526 *	1.080 *, 1.132 *
Attractiveness	0.895 *	0.925 *	0.756 *	1.378 *
Expertise	0.879 *	0.914 *	0.728 *	2.019 *
Trustworthiness	0.905 *	0.933 *	0.777 *	2.008 *
Attitude towards social media influencers	0.913 *	0.938 *	0.792 *	1.132 *
Attitude towards products or services	0.925 *	0.953 *	0.870 *	

Symbol "*" means: DG rho—Dillon–Goldstein's rho > 0.7; CR—composite reliability > 0.6; AVE—average variance extracted > 0.5; VIF—variance inflation factors < 5.

5.3.4. Reliability Analysis

There are two primary methods used to establish construct reliability (i.e., repeatability)—Dillon–Goldstein's rho (DG rho, or rho_A in Smart PLS) and composite reliability (CR). For adequate reliability, both the DG rho and CR values should exceed 0.7 [83]. Here, the DG rho ranged from 0.884 to 0.953, while the CR ranged from 0.931 to 0.970 (Table 5); therefore, the DG rho and CR values for all constructs in the model are acceptable. All constructs have adequate reliability coefficients.

5.3.5. Construct Validity

Two forms of validity assessment—convergent validity and discriminant validity—are essential for establishing construct validity.

5.3.6. Convergent Validity

Convergent validity evaluates the consistency across multiple measures of a single concept. The average variance extracted (AVE) was computed to gauge the convergent validity of the construct, with a minimum threshold of 0.5 [84]. The AVE values for all constructs were determined as significant, affirming the robust convergent validity of the model (Table 5).

5.3.7. Discriminant Validity

Discriminant validity pertains to the ability to distinguish the measures of separate concepts from one another.

5.3.8. Fornell and Larker Criterion

As per Fornell and Larcker's criterion, discriminant validity is affirmed when the square root of the average variance extracted (AVE) for each construct surpasses its correlation with all other constructs. The study findings reveal that the square root of the AVE (italicized) for each construct exceeds its correlation with other constructs (as detailed in Table 6). Hence, compelling evidence is provided to confirm discriminant validity.

Table 6. Discriminant validity—Fornell and Larker criterion.

Factor	Attitude towards SMI	Attitude towards Products/Services	Attractiveness	Convenience	Credibility	Expertise	Trustworthiness
Attitude towards SMI	*0.890*						
Attitude towards products/services	0.684	*0.933*					
Attractiveness	0.403	0.363	*0.869*				
Convenience	0.550	0.478	0.377	*0.915*			
Credibility	0.341	0.335	0.789	0.271	0.726		
Expertise	0.253	0.295	0.484	0.194	0.873	*0.853*	
Trustworthiness	0.197	0.170	0.479	0.101	0.841	0.688	*0.881*

Note: Italics represent the square root of AVE.

5.3.9. Cross-Loadings

The cross-loadings assessment determines whether an item, assigned to a specific construct, displays a higher loading on its designated construct compared to others in the model. The results of this study (as depicted in Table 7) demonstrate that all item factor loadings exhibit stronger associations with their respective constructs (italicized), rather than with other constructs. Hence, based on the examination of cross-loadings, discriminant validity can be confirmed.

Table 7. Discriminant validity—cross-loadings.

Indicator Variable	Attitude towards SMI	Attitude towards Products/Services	Attractiveness	Convenience	Credibility	Expertise	Trustworthiness
AS1	*0.894*	0.601	0.356	0.507	0.299	0.214	0.174
AS2	*0.919*	0.602	0.384	0.501	0.331	0.239	0.206
AS3	*0.912*	0.636	0.346	0.52	0.262	0.185	0.121
AS4	*0.831*	0.594	0.349	0.428	0.323	0.264	0.202
AP1	0.641	*0.934*	0.367	0.489	0.318	0.264	0.150
AP2	0.629	*0.942*	0.311	0.442	0.302	0.274	0.158
AP3	0.642	*0.921*	0.336	0.406	0.317	0.287	0.167
AR1	0.324	0.290	*0.878*	0.275	*0.709*	0.448	0.438
AR2	0.291	0.289	*0.885*	0.335	*0.719*	0.439	0.476
AR3	0.451	0.417	*0.883*	0.432	*0.684*	0.421	0.402
AR4	0.341	0.265	*0.830*	0.266	*0.627*	0.369	0.343
CO1	0.518	0.461	0.337	*0.923*	0.229	0.152	0.082
CO3	0.457	0.387	0.357	*0.891*	0.269	0.199	0.110
CO5	0.532	0.459	0.342	*0.931*	0.25	0.184	0.088
EX1	0.301	0.317	0.445	0.202	*0.765*	*0.861*	0.599
EX2	0.216	0.263	0.431	0.174	*0.800*	*0.906*	0.654
EX3	0.109	0.155	0.345	0.093	*0.703*	*0.840*	0.559
EX4	0.229	0.265	0.425	0.188	0.707	*0.802*	0.532
TR1	0.142	0.114	0.387	0.052	0.756	0.633	*0.902*
TR2	0.126	0.122	0.402	0.034	0.761	0.630	*0.909*
TR3	0.199	0.174	0.439	0.126	0.736	0.570	*0.859*
TR4	0.232	0.192	0.466	0.15	0.713	0.594	*0.854*

5.3.10. Heterotrait–Monotrait Ratio (HTMT)

The HTMT (heterotrait–monotrait) ratio assesses the correlation between constructs in order to ensure discriminant validity. Although the threshold for HTMT varies in the literature, usually ranging from 0.85 to 0.9, the results of this study (as shown in Table 8) reveal that the HTMT ratios for the constructs are below the recommended threshold of 0.9, while also being statistically significant.

Table 8. Discriminant validity—HTMT.

Factor	Attitude towards SMI	Attitude towards Products/Services	Attractiveness	Convenience	Credibility	Expertise	Trustworthiness
Attitude towards SMI							
Attitude towards products/services	0.745						
Attractiveness	0.449	0.399					
Convenience	0.604	0.521	0.42				
Credibility	0.377	0.365	0.884	0.303			
Expertise	0.282	0.326	0.545	0.218	0.973		
Trustworthiness	0.219	0.187	0.532	0.115	0.923	0.773	

5.3.11. Path Coefficients and Evaluation of the Structural Model—Hypotheses Testing

The p-values of the model constructs indicate: (1) the moderate impact of both convenience and credibility on attitude towards social media influencers; and (2) the significant impact of both credibility and attitude towards social media influencers on customer attitude towards products or services. All p-values are below 1%, except the p-value for the influence of credibility on attitude towards products or services, the value of which is below 5% (as shown in Figure 8 and Table 9). These findings align with our hypotheses and with previous research. The regression coefficients for all predictor variables are positive.

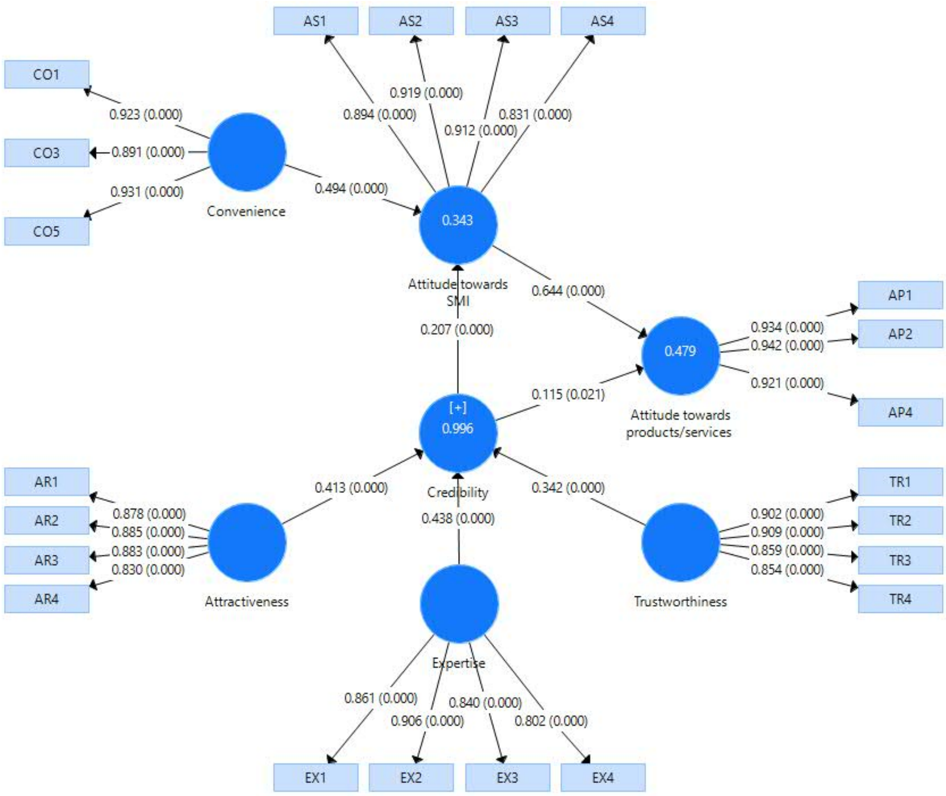

Figure 8. Path coefficients and *p*-values—inner and outer models.

Table 9. The path coefficients of the relationship between latent variables.

Hypothesis	β	Sample Mean	SD	t Statistics	*p*-Values	R^2	Q^2
Attitude towards SMI → Attitude towards products/services	0.494	0.497	0.055	8.910	0.000	0.343	0.268
Attractiveness → Credibility	0.207	0.202	0.050	4.117	0.000		
Convenience → Attitude towards SMI	0.644	0.643	0.051	12.643	0.000	0.479	0.411
Credibility → Attitude towards SMI	0.115	0.116	0.050	2.317	0.021		
Credibility → Attitude towards products/services	0.413	0.413	0.015	27.173	0.000		
Expertise → Credibility	0.438	0.438	0.014	32.326	0.000	0.996	0.520
Trustworthiness → Credibility	0.342	0.342	0.013	25.990	0.000		

In terms of the structural model, the pathways of credibility → attitude towards SMI and credibility → attitude towards products/services show a weak effect, while attitude towards SMI → attitude towards products or services and convenience → attitude towards SMI relationships demonstrate a slightly more significant influence (Table 9). The Q^2 values indicate the good predictive performance of the model, with all values being above zero.

We found no mediating effects of demographics on the construct relationships, except one—educational level. Educational level statistically significantly alters the causal effect relationship between credibility and attitude towards social media influencers, where the coefficient β is -0.090 with a *p*-value of 0.040.

Step 5. Interpret the obtained results.

Our reasons for rejecting the effects of interactivity (H_2) (Figure 8) can be explained by the fact that our young respondents perceived interactivity with social media influencers as something to be taken "for granted". Interactivity has been an inherent and expected capability of websites since the emergence of the web. Social media platforms have evolved to facilitate and encourage this interaction through features such as comments, likes, direct messages, and live streams. As a result, users have grown accustomed to engaging directly with influencers, asking questions, sharing opinions, and forming relations, making interactivity with influencers a standard and integral part of the social media experience. In contrast, individuals from older generations or different cultural backgrounds may not have grown up with social media and may not intuitively expect or value the same level of interactivity with influencers as younger, more digitally native individuals. For this reason, the findings of some previous studies [40,47] do not confirm our hypothesis regarding the presumed presence of the interactivity of social media. It is also noteworthy that the beta coefficient of interactivity from the SEM model of Ooi et al. [47] is negative, indicating a negative relationship between interactivity and the attitude towards social media influencers. In other words, as the level of interactivity with social media influencers increases, the attitude regarding them tends to decrease. This could imply that excessive or intrusive interactivity may lead to decreased favourability towards or trust in influencers, possibly due to perceptions of over-promotion, lack of authenticity, or invasion of privacy.

The factors contributing to the rejection of the effects of attitude towards influencers (H_6) and attitude towards products or services (H_7) on purchase intention (Figure 8) can be attributed to the specific context of our study. A well-known fact in Bulgarian social psychology is that Bulgarians tend to be particularly sceptical and mistrustful of the unknown. This cautiousness often has its roots in historical and cultural factors. Some historical periods may have played a role in shaping this distrust among Bulgarians. Additionally, the economic situation and corruption in society can further erode consumer trust. These factors collectively contribute to a cultural framework that fosters mistrust and scepticism, ingraining them as common elements of the societal mentality. Unlike in Bulgaria, developed nations are characterized by the so-called "keeping up with the Joneses" phenomenon. This phenomenon is particularly widespread in countries with high levels of individualism, consumer culture, and social media usage, where people tend to compare themselves with others and strive to maintain or enhance their social status through excessive consumption.

After the elimination of the interactivity construct (H_2) from the unfitted model, social media convenience (H_1) indicated a positive relationship (Figure 8, $\beta = 0.494$ and $p < 0.001$) with attitude towards influencers. Convenience encourages user engagement and retention on social media platforms. When users find it easy and convenient to access and interact with the content, engage with other followers or viewers, or perform tasks such as shopping for products or booking services, they are more likely to spend time on the platform and return in the future. This result is in line with research that showed this variable as one of the main determinants of the attitude towards influencers [39,43,46,47].

The result of H_3 testing, which is the effect of credibility, shows that its measures can reflect the user's attitude towards influencers ($\beta = 0.207$ and $p \leq 0.001$). Credibility significantly affects user attitudes towards influencers for several reasons. Credible influencers are more likely to be seen as authentic sources of information or recommendations. The credibility of influencers shapes the users' perceptions of their content and recommendations. Credible influencers foster trust with their audience over time, leading to stronger relationships and loyalty. Our results are in line with the results of previous studies by Lim et al., Yuan and Lou, Pham et al., Ata et al., Niloy et al., and Ooi et al. [39,42–44,46,47].

A similar situation occurs with the influence of credibility on attitude towards products or services (H_4). The credibility of social media influencers also significantly shapes users' attitudes towards advertised products or services ($\beta = 0.151$ and $p < 0.05$). The endorsements of credible influencers hold greater weight and effect among their followers. Influencers' positive perceptions extend to the advertised products, resulting in more favourable attitudes and an increased likelihood of purchase. Our results confirm the results obtained by Xiao et al., Chekima et al., Yuan and Lou, Ooi et al., Al-Sous et al., and Coutinho et al. [40–42,47–49]

According to the results of the H_5 testing, related to the impact of attitude towards influencers (β = 0.644 and p < 0.001), this factor can positively influence the user's attitude towards products or services. As previously demonstrated, users often view social media influencers as credible sources of information. Consequently, their favourable attitude towards influencers may result in a more favourable attitude towards the products or services endorsed by those influencers. Users tend to associate themselves with influencers whose values, lifestyles, or preferences align with their own. Users often develop emotional relationships with the influencers they follow, which can shape their attitudes towards advertised products or services. This finding is consistent with the significance of the same factor in the models created by Yuan and Lou and by Ooi et al. [42,47].

Our testing supports H_8 regarding educational level, unlike the rest of the moderating sub-hypotheses. For the above-mentioned path between credibility and attitude towards influencers, individuals that are more educated are less reliant on influencer credibility in comparison to their counterparts. Higher education often fosters critical thinking skills, allowing individuals to assess information more critically and discern the credibility of sources. Educated individuals are more sceptical of influencers' claims and endorsements, i.e., they place smaller importance on influencer credibility as a factor in their attitudes.

The R^2 values, as shown in Table 9, are 0.343 and 0.479, indicating that roughly 34% and 48% of the variability in customer attitudes towards influencers and products can be explained by the following predictor variables: social media convenience and source credibility. The remaining variability can be attributed to various other factors.

In addition to the classic one-order construct SEM approach, in line with the source credibility theory, our data analysis also includes a second-order construct also known as credibility, comprising attractiveness (AT), expertise (EX), and trustworthiness (TR), employing both the embedded and disjointed approaches for the investigation of higher-order constructs.

5.4. Other Models of Customer Attitudes towards Social Media Influencers

To elucidate the relationships between the input and output constructs, we employed four ML algorithms, as depicted in Table 10. The mean square error (MSE) signifies the disparity between the assessed and actual output values of the model, while the mean absolute error (MAE) is calculated as the average of the absolute differences between the predicted and actual values. AdaBoost consistently outperformed the other ML techniques across all evaluation metrics, followed by the random forest and decision tree techniques.

Table 10. Results of using ML algorithms to model user attitudes towards influencers.

ML Method	MSE	MAE	R^2
Decision Tree	0.002	0.006	0.997
SVM	0.094	0.181	0.876
Random Forest	0.001	0.009	0.998
AdaBoost	0.000	0.002	0.999

While SEM models demonstrate a considerably smaller R^2 value compared to machine learning models, their advantage lies in the interpretability of their predictions. Conversely, while ML models boast higher accuracy (ranging from 0.876 to 0.999), their predictions often lack transparency and prove challenging to interpret. Thus, the selection between these models hinges on the specific purpose of the data analysis.

Using the coefficients derived from the SEM model, we can employ multi-criteria decision-making (MCDM) methods such as the technique for order of preference by similarity to the ideal solution (TOPSIS) and an evaluation based on the distance from the average solution (EDAS). These methodologies facilitate the computation of composite indices for a comprehensive assessment of user satisfaction with social media marketing.

6. Conclusions and Future Research

Social media marketing has revolutionized business–customer interactions, providing various platforms for online engagement. By delivering valuable content in an interactive manner, social media influencers bridge the gap between brands and consumers, empowering companies to transform their advertising strategies and extend their reach beyond geographical constraints. This digital marketing tool enhances business-to-customer relationships by facilitating collaboration and efficiency in interactions.

In this study, we explore the characteristics of social media influencers, highlighting their transformative effect on brand perception and consumer behaviour. The key findings are outlined below:

- An online survey was conducted to gather data on customer perceptions and attitudes towards social media influencers. A demographic analysis of the survey data revealed that the majority of respondents (98%) resided in urban areas, with 60% being under 40 years old, and 74% being female. Nearly all respondents (96%) reported using social media daily. In terms of education, the respondents were evenly distributed between high school and higher educational levels (bachelor's, master's, or doctoral studies). Analysis of customer sentiment in their opinions showed that a majority (66%) expressed positive attitudes towards social media influencers as a convenient tool for online marketing. Only a quarter (25%) of the respondents did not have favourite influencers.
- The customers were grouped into two statistically significant clusters. The first cluster consisted of respondents who reported higher levels of satisfaction in perceived convenience, satisfaction in social media influencer activities, satisfaction in products or services advertised, and perceived attractiveness. Conversely, the second cluster included those with a relatively low level of purchase intention, satisfaction with influencers' experience, trustworthiness, and interactivity.

The theoretical causal first- and second-order SEM models revealed several dependencies:

- There are statistically significant impacts of perceived convenience (H_1) and source credibility (H_3) on attitudes towards influencers.
- There are statistically significant effects of perceived source credibility (H_4) and attitude towards influencers (H_5) on attitudes towards products or services.
- There are no statistically significant consequences of perceived interactivity (H_2) on customer attitudes towards influencers.
- There are no statistically significant dependencies of attitudes towards influencers (H_6), attitudes towards products/services (H_7), and purchase intention.
- Additionally, our analysis of the hypothesis H_8 indicated that customers' attitudes and purchase behaviour were not significantly affected by demographic factors such as age, gender, educational level, and place of residence. The only factor found to have a significant negative mediating effect on customers' attitudes towards social media influencers was their educational level.

Our contributions to the field of social media marketing include identifying the key drivers behind consumer attitudes and purchase behaviour resulting from digital influencer activities. Additionally, we propose models that practitioners can utilize to develop effective strategies to promote the adoption of social media advertising through online influencers.

Social media influencer marketing offers numerous advantages for both small and medium enterprises (SMEs) and global corporations. For SMEs, collaborating with influencers provides an opportunity to increase brand awareness and reach a larger audience without the need for a substantial marketing budget. Additionally, influencer collaborations allow SMEs to target niche markets that attract specific demographics more effectively. For global companies, social media influencer marketing offers a scalable approach to reaching diverse audiences across different regions and markets. By partnering with mega influencers, large corporations can enhance brand awareness on a mass scale and communicate with their target audience. Furthermore, influencer marketing allows global companies to stay agile and adapt their marketing strategies to different cultural contexts and consumer preferences worldwide. Overall, leveraging social media influencers can provide both SMEs and global companies with a competitive edge in today's digital landscape.

This study has the following limitations: (1) the sample size and its attributes might not adequately represent diverse demographic perspectives; (2) user perceptions are multi-faceted and may involve various psychological, social, and cultural factors, which were not included in our analysis; and (3) the study solely focused on individual user attitude, excluding inputs from marketing experts and business representatives. These limitations may result in an incomplete portrayal of the broader social media marketing landscape, potentially overlooking valuable insights and challenges.

Our plans for future research include:

(1) Increasing the participant pool in our survey to encompass additional participants, including the unexplored behaviours of Generation Alpha;
(2) Examining not only the direct relationships between variables but also their indirect effects in the context of SEM, while understanding the overall impact of one variable on another;
(3) Comparing our results with similar studies from other countries, with a focus on the spread of social media influencer marketing and the moderation effect of different socio-economic indicators such as income and region;
(4) Exploring the changes and evolution of social media marketing in a post-COVID-19 environment.

Additionally, we plan to conduct further analyses by implementing fuzzy multi-criteria decision-making methods to determine the multi-attribute cause-and-effect interdependencies between factors that affect customer satisfaction in e-influencer advertising. Future research aims to ensure that social media, as a burgeoning advertising platform, remains accessible to users of all demographics, fostering ethical and socially responsible digital transformations that can enhance customer value.

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