Designing a Model of the Relationship Between Advertising Content Risks in Social Networks

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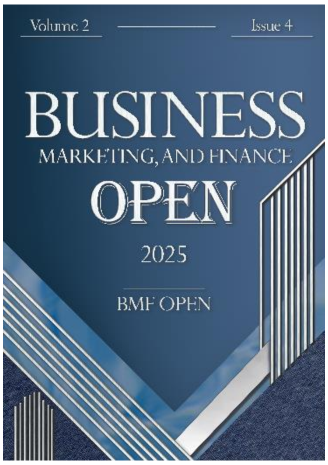

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Abstract: With the rapid growth of social media, purchasing risks have also increased, and these concerns influence consumer purchasing behavior. In this regard, the present study identifies and models the risks associated with advertising content in social networks using both qualitative and quantitative approaches. This study was conducted for reputable brands in Iran. The research population consisted of experts, including marketing researchers and marketing managers of brands active in social media marketing, who were selected through purposive non-probability sampling using the snowball technique, resulting in a total of 25 participants. Through a semi-structured interview process with experts, qualitative data were collected and coded using content analysis. The results indicated that the model includes "functional risk," "content risk," "operational risk," "security and privacy risk," "product risk," "technology risk," "environmental risk," and "behavioral purchase intention." Subsequently, quantitative data were collected through a pairwise comparison questionnaire and analyzed using the interpretive–structural modeling (ISM) method to develop the model. The findings of the interpretive–structural modeling showed that "environmental risk," "technology risk," "product risk," and "security and privacy risk" exert the highest influence, while "functional risk" has the lowest influence on behavioral intention in social networks. Therefore, managers must manage and control the influential risks to encourage customers to make purchases.

Keywords: risks, advertising, social networks.

1. Introduction

The rapid evolution of digital technologies and the pervasive expansion of social media platforms have dramatically transformed how consumers interact with brands, access information, and make purchasing decisions. As social networks become increasingly integrated into daily life, advertising content disseminated through these platforms has emerged as one of the most influential tools for shaping consumer attitudes, perceptions, and behavioral intentions. Yet, this environment is also characterized by heightened uncertainty, information overload, and multiple forms of perceived risk that directly affect how individuals evaluate online advertising content. In many cases, these risks undermine trust, distort value perceptions, and ultimately hinder customers' willingness to engage with purchasing activities through social media channels. The need to systematically understand and model these diverse risks has therefore become an essential priority for researchers and practitioners alike [1].

Recent studies highlight that the information ecosystem of social networking platforms is shaped by dynamic interactions, real-time content creation, algorithmic curation, and participatory communication, all of which influence consumer sensemaking processes [2]. These platforms foster immersive environments where individuals interpret, negotiate, and make judgments about brand messages, but the complexity of these environments also amplifies perceived risks associated with content accuracy, source credibility, privacy protection, and product authenticity. Within the broader digital advertising landscape, social media advertising stands out for its interactivity and personalization; however, these strengths can simultaneously create vulnerabilities that result in consumer skepticism or avoidance behaviors [3]. As a result, understanding advertising content risks requires analytical approaches that simultaneously consider psychological, technological, environmental, and operational dimensions.

From a business and marketing perspective, identifying and mitigating social media advertising risks is critical for ensuring customer engagement, loyalty, and purchase intention. Research shows that social media interactions strongly shape consumers' emotional responses, cognitive evaluations, and behavioral engagement with brands [4]. However, risks associated with misleading advertising content, privacy violations, data misuse, or low-quality promotional materials can reduce consumers' confidence and deter them from making purchases online. Studies indicate that social media users perceive risks not only in terms of privacy intrusion but also in relation to the reliability of content, the transparency of advertiser intentions, and the perceived trustworthiness of messages [5]. These risks vary across cultural, technological, and regulatory contexts, making it essential for brands to understand their multifaceted nature.

Scholars emphasize that consumer attitudes toward online advertising are influenced by the interplay between content characteristics, platform features, and user traits [6]. For instance, programmatic advertising, algorithm-driven content delivery, and influencer-generated promotional messages can enhance or diminish perceived usefulness and credibility depending on how transparent, relevant, and personalized they appear. Research also reveals that consumer attitudes are shaped by risks related to content clarity, message quality, information accuracy, and the authenticity of brand-consumer interactions [7]. When such risks are high, customers may begin avoiding advertisements or relying on electronic word-of-mouth (eWOM) to compensate for perceived uncertainty. This aligns with findings showing that trust, perceived risk, and eWOM collectively shape online shopping outcomes [8].

Social media platforms are also central to shaping brand loyalty, brand consciousness, and relational engagement. Yet, these positive outcomes depend heavily on the effectiveness and credibility of advertising content. Studies demonstrate that social media addiction, excessive exposure to promotional messages, and information fatigue can weaken users' attitudes toward online advertising, ultimately reducing purchase intention [9]. Similarly, misaligned advertising strategies, low-quality visuals, or aggressive promotional tactics can negatively affect consumer brand perceptions, undermining long-term loyalty [10]. Therefore, addressing the risks associated with advertising content becomes crucial for preserving the integrity and strategic effectiveness of social media marketing campaigns.

In recent years, the literature has increasingly examined how technological and environmental factors contribute to advertising risks. Technological shortcomings such as low-quality content, broken links, insufficient platform reliability, or outdated information may lower consumers' confidence in the advertising message. The growing use of artificial intelligence and algorithms in content distribution also introduces unique risks, including bias, misleading personalization, and lack of transparency [11]. From an environmental perspective, exposure to inappropriate cultural symbols, offensive messaging, or content that contradicts local social norms can generate negative reactions among consumers, particularly in culturally sensitive markets [12]. These factors illustrate how broader environmental and technological contexts influence risk perceptions beyond the content itself.

Contemporary studies show that perceived risk remains one of the strongest determinants of consumers' online purchase intention, influencing decision-making processes across multiple product categories and demographic contexts. For instance, research on online food purchasing reveals that concerns over privacy, transaction security, product quality, and information reliability substantially impact consumer willingness to buy from digital platforms [13]. Similar findings in e-commerce systems demonstrate that social media advertising can shape both purchase intention and customer loyalty when risks are properly managed [14]. However, when consumers face uncertainty or lack of trust, they tend to delay purchases or seek alternative offline channels.

From a strategic communication standpoint, advertising content must be aligned with brand reputation, message clarity, and ethical communication standards. However, challenges such as greenwashing practices, misinformation, or ambiguous claims have been shown to erode trust and intensify perceived risk [15]. The significance of risk transparency is further highlighted in studies examining privacy paradoxes, where consumers express concern about privacy yet frequently disclose personal data online due to platform pressures or information asymmetries [16]. Thus, achieving message transparency and ethical communication is fundamental to reducing risk perceptions and influencing purchase decisions.

Moreover, social media advertising is increasingly shaped by influencer marketing, electronic word-of-mouth, and user-generated content. Although these mechanisms can enhance credibility, they also introduce risks related to influencer authenticity, message manipulation, and unclear sponsorship disclosures [17]. Evidence shows that influencer credibility can significantly boost purchase intention, but deceptive practices or nontransparent advertising can have the opposite effect [18]. At the same time, customer engagement behaviors depend on the perceived trustworthiness and relevance of advertising content, highlighting the need for advertisers to maintain consistency between message intent and audience expectations [19].

Risk assessment models have gained importance in recent years as scholars seek robust frameworks capable of handling complex, multidimensional phenomena. The fuzzy Delphi method, interpretive structural modeling (ISM), and MICMAC analysis are among the most effective tools for measuring and prioritizing risks in ambiguous or uncertain contexts [20]. Studies applying ISM in supply chains, circular economy initiatives, and consumer behavior show that it is a powerful method for examining hierarchical relationships among risk factors [21]. In marketing and behavioral studies, ISM enables researchers to reveal how different dimensions of perceived risk interact and influence consumer decision-making processes [22]. These methodological approaches are particularly useful for analyzing advertising content risks, which are often interrelated, multidimensional, and influenced by contextual variables.

Research also highlights the importance of understanding social and psychological implications of digital advertising, particularly following global events such as the COVID-19 pandemic. The pandemic brought new forms of social and technological uncertainty, reshaping consumer trust, digital engagement, and risk perceptions in online environments [23]. In the context of university students, educators, and digital systems, studies show the importance of readiness, digital literacy, and structured frameworks to navigate information risks and technological challenges [24]. Meanwhile, broader investigations in disaster preparedness and corporate social responsibility reveal how institutional communication, trust, and social expectations influence risk evaluations in online ecosystems [1]. These insights make it increasingly important to assess advertising content risks within broader social, technological, and cultural systems.

In addition to technological and social risks, consumer-related factors play a significant role in shaping responses to advertising content. Consumers rely heavily on emotional cues, mental shortcuts, and social proof when evaluating online content. However, misleading advertising, unfounded claims, or confusing promotional messages can distort consumer cognition, leading to stress, decision fatigue, and avoidance behaviors [7]. Furthermore, online behavior is shaped by brand consciousness, personal motivation, and cultural norms, which can amplify or diminish the effects of perceived risk [25]. As these dynamics become more intricate, it is essential to develop analytical frameworks that integrate multiple risk types—functional, operational, content-related, technological, environmental, and privacy-related.

Another significant body of literature emphasizes the role of environmental and cultural determinants in shaping perceived risks associated with digital advertising. Environmental advertising, cultural sensitivity, and the visual symbolism of promotional content can influence consumer reactions in nuanced ways, particularly in markets with strong cultural orientations [26]. Similarly, political and regulatory environments shape consumers' perceptions of safety, fairness, and ethical responsibility in online advertisements. These macro-level influences underscore the importance of evaluating social media advertising risks within broader socio-cultural and regulatory contexts.

Despite the growing volume of digital advertising research, there remains limited theoretical and empirical clarity concerning the hierarchical relationships among advertising content risks in social networks. Much of the existing literature examines isolated aspects of risk—such as privacy, trust, or credibility—without developing integrated models that illustrate how these risks influence one another and ultimately shape consumer behavioral intention. Addressing this theoretical gap requires approaches that can uncover hidden structures, explore interdependencies, and identify the most influential risk factors within a complex system. Interpretive Structural Modeling and MICMAC analysis offer powerful tools for achieving these goals, as demonstrated in previous studies across marketing, operations, and behavioral sciences [27, 28].

Given the growing prevalence of social media advertising and the increasing complexity of digital ecosystems, there is an urgent need for a comprehensive risk model that captures the diverse factors shaping consumer purchase behavior in online environments. Such a model can support academics in advancing theoretical understanding, while also guiding practitioners in designing safer, more effective advertising strategies that enhance trust, relevance, and consumer engagement. Considering the multidimensional risks associated with advertising content—including technological, environmental, product-related, privacy-related, operational, functional, and content-based risks—developing a structured, hierarchical model is essential for illuminating how these factors interact and how they shape consumer behavioral purchase intention.

Therefore, the aim of this study is to design a comprehensive model that identifies, categorizes, and analyzes the hierarchical relationships among advertising content risks in social networks to explain their impact on consumers' behavioral purchase intention.

2. Methodology

Given the growing increase in advertising on social media for the purpose of boosting sales, this study aims to identify and analyze the risks associated with advertising content in social media, as well as to model and develop a theoretical framework. This study was conducted in Iran in 2023. To achieve the research objectives, we employed a qualitative–quantitative study to analyze the data. Because the risks associated with advertising content in social media are not well supported in the theoretical literature, and in order to identify the risks in practice, we used content analysis to identify them. Content analysis is a common research method that identifies indicators, statements, and concepts, enabling the researcher to obtain more relevant and coherent information. Therefore, we used the content analysis method and coding techniques to extract the elements of the model through interviews. In the qualitative section, the researcher seeks to explore the nature of advertising content risks in social networks, which was accomplished by interviewing experts. This study employed both inductive content analysis (expert interviews) and deductive content analysis (theoretical knowledge). Due to the limited existing literature on risks associated with advertising content in social media, inductive content analysis was used.

Since no predetermined qualitative data existed, we used experts and a specialized panel based on the approach of Abbas et al. (2023). The research population consisted of experts, including marketing researchers and marketing managers of brands active in social media marketing. A purposive, theoretical, non-probability sampling method with snowball technique was used, resulting in the selection of 30 individuals. According to Jena et al. (2017), a panel of 12 to 20 members is sufficient to support the data. Abbas et al. (2023) stated that the criteria for selecting experts include relevant theoretical knowledge, practical experience, and the ability to understand the phenomenon. Accordingly, our criteria for selecting experts included holding a postgraduate degree in marketing, possessing theoretical and practical knowledge with at least 20 years of marketing-related experience, sufficient motivation for collaboration, and being accessible.

In accordance with the study of Jandaghi and Beini (2023), the reliability of the content analysis was examined in terms of validity, credibility, and transferability. For validity, sufficient documentation and consultation with specialists were used to verify how the research variables were formed. For credibility, the fuzzy Delphi method was used to confirm the acceptability of the findings. For transferability, interviews were conducted at different locations and times.

The fuzzy Delphi method was used to determine and select the indicators and categories. The purpose of the Delphi method is to utilize the competence and cognitive abilities of experts to achieve the most reliable convergence of opinions across multiple rounds of questionnaires and decision-making. The fuzzy Delphi method integrates fuzzy set logic into the Delphi technique, which is suitable for the ambiguous nature of human reasoning in real-world contexts.

Then, since the relationships between the risks associated with advertising content in social media are not clearly defined, and in order to conduct modeling and develop a conceptual framework, we used the interpretive–structural modeling (ISM) method to develop a structural model that identifies the relationships among the risks. ISM was proposed by Warfield in 1973 for analyzing complex systems. ISM determines the interrelationships among model elements based on expert knowledge to support better decision-making. These relationships are visually and structurally represented to enhance understanding of the phenomena and to identify how one variable influences another. The ISM method has assisted specialists and marketing researchers and has been applied by Tareial et al. (2023), Dadashi Jokandan et al. (2023), and Mustafa and Sharma (2022). Figure 1 presents the flowchart of the research data analysis process.

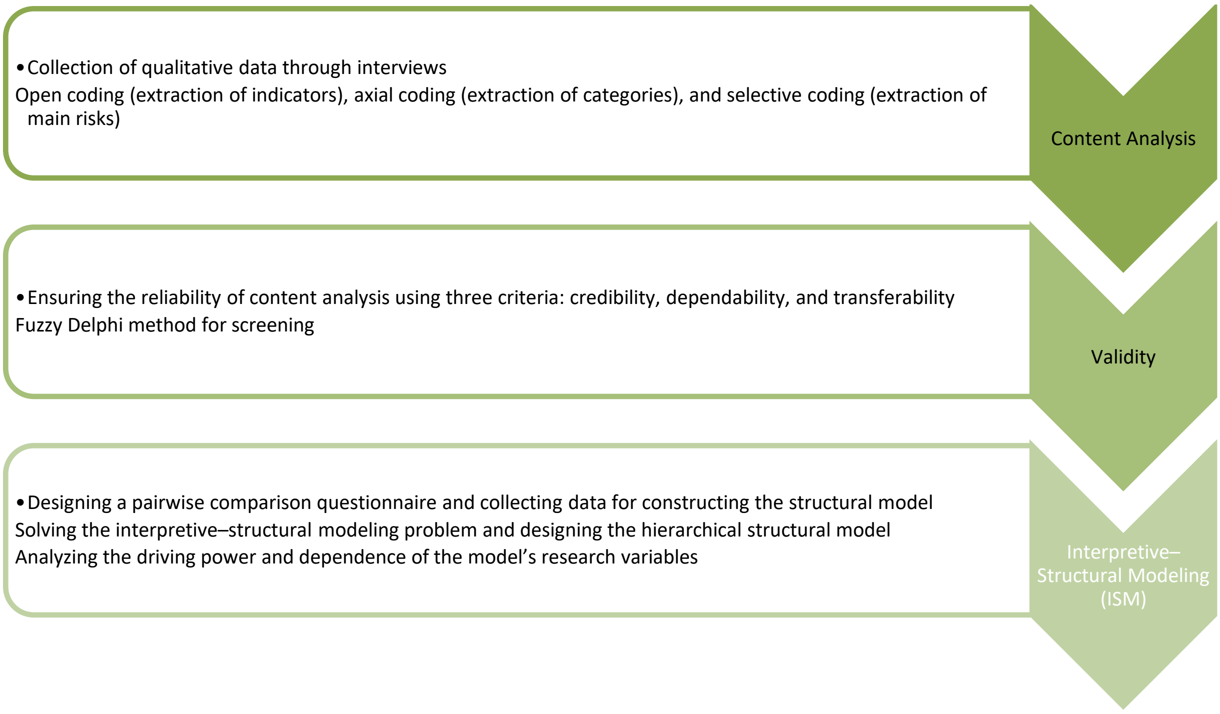

Figure 1. Flowchart of Data Analysis

3. Findings and Results

To identify and extract the risks associated with advertising content in social media, a semi-structured interview was conducted with experts. The interviews were carefully analyzed, key statements were highlighted, and the codes were collected. These codes, referred to as open coding, emerged inductively. Then, the researcher compared the concepts derived from the open coding, and those that were semantically aligned and indicated a common subject were grouped at a higher level through axial coding. The categories were thus formed through a combination of deductive and inductive approaches. In the third level, selective coding, the categories were connected to one another in a new and meaningful structure, and the main classifications were completed, resulting in the identification of the concepts or risks. After coding, a hierarchical structure of the qualitative section—consisting of codes, categories, and concepts—was formed.

In the next step, the fuzzy Delphi method was used to reach a consensus regarding the importance of the risks in the study. The experts determined the degree of importance for each of the identified risks. The fuzzy Delphi method was conducted in three rounds. In the second round, experts expressed their opinions regarding the removal, modification, merging, or addition of new codes, and these opinions were compared with those of the first round. The decision-making criteria in the Delphi process were based on the approach of Karimi Shirazi et al. (2017) and the Pareto 80/20 rule. Accordingly, if the degree of disagreement between the first and second rounds was less than the threshold of 0.2, the survey was stopped; however, variables for which the disagreement exceeded 0.2 were forwarded to the third round of the fuzzy Delphi survey. Codes with an average expert score above 8 were retained, and those with scores below 8 were eliminated. Therefore, the results of the fuzzy Delphi method showed that eight main risks, along with 19 categories and 58 open codes, were selected and confirmed for the final model. Table 1 presents the results of the content analysis and the risks associated with advertising content and behavioral intention in social networks. These risks serve as the input for the interpretive–structural modeling method.

Table 1. Risks of Advertising Content and Behavioral Intention in Social Networks

Main Risks (Concepts)	Sub-Risks (Categories)	Indicators
Security and Privacy Risk	Privacy Risk	Access to personal information – Misuse of personal information – Sharing information without permission – Others' use of my information history
	Security Risk	Threats to asset security – My information being unsafe – Unsafe purchasing
Product Risk	Product/Service Delivery Risk	Risk of only informing rather than delivering goods/services – Incomplete information regarding product/service quality – After-sales service risk
	Product Trust Risk	Risk of product not matching my expectations – Risk of product trust based on advertising content – Unclear product characteristics
	Product Brand Risk	Risk of counterfeit trademarks – Risk of negative interactions or emotions toward the brand – Unreliable brands
Content Risk	Credibility Risk	Hacking of advertising content – Unreal or fake advertising interactions – Fake messages – Rapid deletion of advertising content
	Agency Relationship Risk	Lack of commercial relationship with the advertising content – Unidentifiable commercial relationships in advertising content – Risk of no connection between content and sellers
	Advertising Capability Risk	Projection and dispersion of advertising content – Risk of influencers not understanding product quality – Excessive or confusing content
Technology Risk	Clarity Risk	Inconsistency in formats and templates – Quality risk of advertising content (text, video, image)
	Information Risk	Risk of inaccurate or outdated data – Dissemination of incorrect or misleading information – Poor and low-quality information
Environmental Risk	Social Risk	Cultural ridicule on social networks – Cultural conflict on social networks – Promotion of violence on social networks – Destructive behaviors in advertising content
	Legal Risk	Risk of non-compliance with commercial laws – Risk of non-compliance with legal regulations
Operational Risk	Purchasing Risk	Risk of false excitement due to incentives (price/discount) – Risk of unanswered questions – Risk of returning or replacing goods – Cost-related risks
	Perceived Time-Loss Risk	Excessive time spent viewing advertising content – Excessive time spent comparing advertisements and making decisions – Irrelevant timing of advertisements
Functional Risk	Perceived Ineffectiveness Risk	Losing sight of the goal – Difficulties in purchasing – Lack of customization of consumer needs
	Ambiguity Risk	Risk of exploiting personal emotions – Risk of stress and anxiety – Feeling unsafe during purchasing
	Perceived Value Risk	Risk of inadequate influence for decision-making – Risk of interference in choice
	Relevance Risk	Misalignment of advertisements with my needs – Misalignment with expectations – Risk of not meeting informational needs
Behavioral Purchase Intention	Purchase Intention	Using social networks for purchasing – Purchasing products/services – Willingness to buy

The main risks of social media advertising content listed in Table 1 were selected for modeling using the ISM method. The first stage of ISM is determining the Structural Self-Interaction Matrix (SSIM). To collect the data, a pairwise comparison questionnaire was designed, and the experts evaluated the degree of influence of each element on the others as follows: no influence (0), low influence (1), influential (2), and highly influential (3). The aggregated responses of the 30 experts were calculated, and the Structural Self-Interaction Matrix was obtained, as presented in Table 2.

Table 2. Structural Self-Interaction Matrix (SSIM)

Variable	Security & Privacy Risk	Product Risk	Content Risk	Technology Risk	Environmental Risk	Operational Risk	Functional Risk	Behavioral Purchase Intention
1	0	28	34	21	39	32	36	27
2	46	0	55	53	61	60	48	45
3	38	39	0	26	29	33	35	27
4	40	30	21	0	31	35	39	40
5	53	34	52	54	0	47	29	28
6	58	40	50	53	32	0	30	31
7	52	29	49	40	48	50	0	28
8	49	25	48	61	60	59	60	0

In the second stage, the Structural Self-Interaction Matrix was converted into a binary (0–1) matrix called the Initial Reachability Matrix. According to Ocampo et al. (2022), a threshold value was defined to construct the Initial Reachability Matrix. This threshold was obtained by multiplying the number of experts (30) by the influence intensity of the pairwise comparison scale (2), which yielded a value of 60. This number represents the average level of influence among the risks. Therefore, consistent with Ocampo et al. (2022), if any influence score in Table 2 was greater than 60, the risk was considered influential and assigned a value of 1; otherwise, it was assigned a 0 (no influence).

In the third stage, the Final Reachability Matrix was developed. In the Final Reachability Matrix, indirect relationships among risks are identified. The consistency rule is as follows: if element A influences B (value = 1) and B influences C (value = 1), then C must also influence A (value = 1). These calculations were performed using MS Excel and Boolean logic, and the Final Reachability Matrix was produced. The results are presented in Table 3.

Table 3. Final Reachability Matrix

Variable	Security & Privacy Risk	Product Risk	Content Risk	Technology Risk	Environmental Risk	Operational Risk	Functional Risk	Behavioral Purchase Intention	Driving Power
1	1	0	1	0	0	1	1	1	5
2	0	1	1	0	0	1	1*	1	5
3	0	0	1	0	0	0	1	1	3
4	0	0	1	1	0	1	1	1	5
5	0	0	1	0	1	1	1*	1	5
6	0	0	1	0	0	1	1	1	4
7	0	0	0	0	0	0	1	1	2
8	0	0	0	0	0	0	0	1	1
Dependency Power	1	1	6	1	1	5	7	8	

In the fourth stage, to classify the risks and build the structural model, the driving and dependence power of each risk was calculated using the Final Reachability Matrix, as shown in Table 3. Then, based on Karimi Shirazi et al. (2017) and the DEMATEL method (Si et al., 2018), the net driving/dependence power of each risk was computed. Based on the resulting values, the risks were ranked in descending order. Dependent risks appear at the lower levels of the model, driving risks appear at higher levels, and risks with equal influence are placed in the same level. These findings are presented in Table 4.

Table 4. Level Partitioning of Advertising Content Risks and Behavioral Intention in Social Networks

Risks	D (Driving Power)	R (Dependence Power)	D–R	Level	Result
Behavioral Purchase Intention	1	8	–7	1	Dependent
Functional Risk	2	7	–5	2	Dependent
Content Risk	3	6	–3	3	Dependent
Operational Risk	4	5	–1	4	Linkage
Security & Privacy Risk	5	1	4	5	Independent
Product Risk	5	1	4	5	Independent
Technology Risk	5	1	4	5	Independent
Environmental Risk	5	1	4	5	Independent

In the fifth stage, after determining the relationships and levels of risks, they were illustrated as a structural model based on Table 4, as shown in Figure 2.

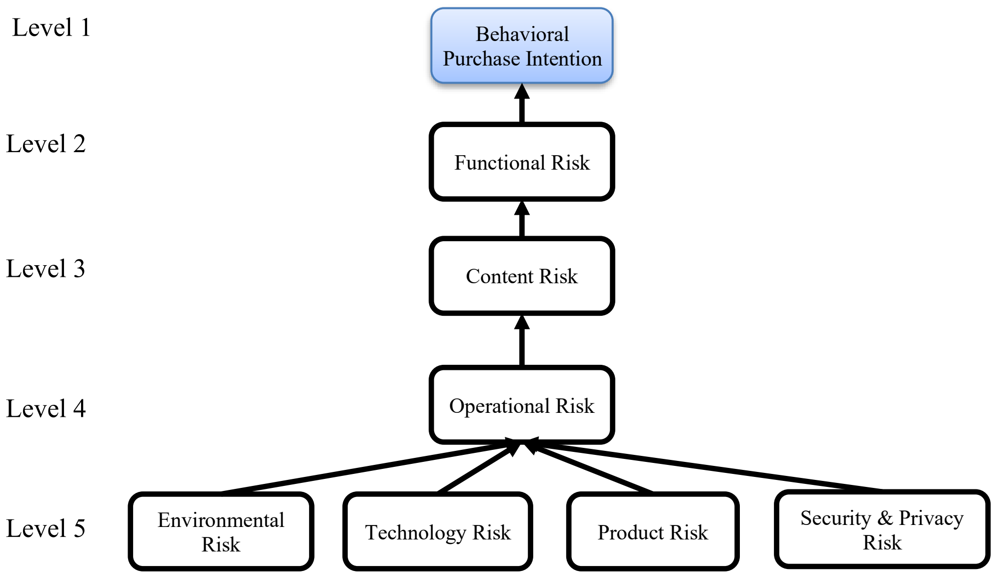

Figure 2. Interpretive–Structural Model (ISM) of Advertising Content Risks and Behavioral Intention in Social Networks

As shown in Figure 2 and Table 4, the risks of advertising content and behavioral intention in social networks are classified into five levels. At Level 5, "Environmental Risk," "Technology Risk," "Product Risk," and "Security and Privacy Risk" are placed, representing the strongest influence on behavioral intention in social networks. These risks are not interrelated, but they influence the level below them.

At Level 4, "Operational Risk" is located, which influences the third level, "Content Risk." At Level 2, "Functional Risk" appears, which is influenced by higher risks but affects the lowest level. At Level 1, "Behavioral Purchase Intention" is placed, representing the outcome of consumers' perceptions of advertising content risks in social networks.

In the sixth stage of ISM, the type of risks in the model was identified using MICMAC analysis. The purpose of MICMAC is to determine and examine the driving power and dependence power of risks. Figure 3 presents the related findings. Based on driving and dependence power, risks were classified into four groups:

1. **Group 1 (Autonomous):** No risks are located in this area, indicating strong interconnectedness among the risks. This group typically includes variables with weak driving and weak dependence power.

2. **Group 2 (Dependent):** This category includes “Behavioral Purchase Intention,” “Functional Risk,” and “Content Risk.” These risks have weak driving power but strong dependence power. Managing and controlling these risks primarily leads to consumers’ behavioral purchase intention in social networks.
3. **Group 3 (Linkage):** “Operational Risk” falls into this group, characterized by strong driving and strong dependence power. Any change in this risk can affect the entire system of risks.
4. **Group 4 (Independent):** Four risks—“Security and Privacy Risk,” “Product Risk,” “Technology Risk,” and “Environmental Risk”—are placed in this group. These variables have strong driving power and weak dependence power. They drive the system and require greater managerial attention.

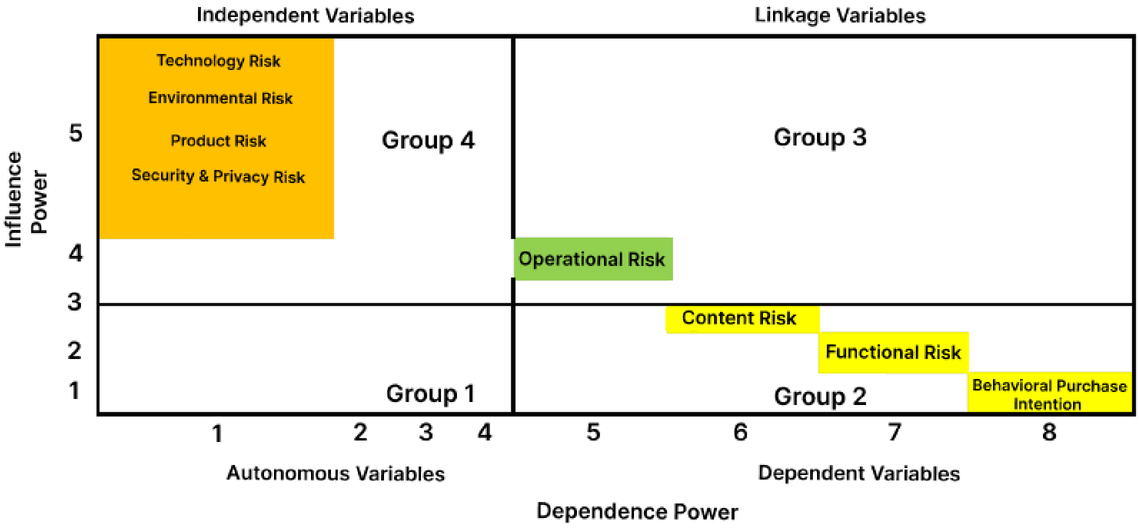

Figure 3. MICMAC Classification of Advertising Content Risks and Behavioral Intention in Social Networks

4. Discussion and Conclusion

The purpose of this study was to identify, categorize, and structurally model the risks associated with advertising content in social networks and to explain their hierarchical relationships and influence on consumers’ behavioral purchase intention. The findings, derived from content analysis, fuzzy Delphi screening, interpretive structural modeling (ISM), and MICMAC analysis, revealed eight primary risks—security and privacy risk, product risk, content risk, technology risk, environmental risk, operational risk, functional risk, and behavioral purchase intention. These risks were arranged across five hierarchical levels, demonstrating that environmental, technological, product, and security/privacy risks exert the strongest influence (Level 5), followed by operational risk (Level 4), content risk (Level 3), functional risk (Level 2), and ultimately behavioral purchase intention (Level 1). The MICMAC results further supported this hierarchy by categorizing risks into independent, linkage, dependent, and autonomous zones, revealing strong interdependencies among risk categories. These results collectively demonstrate that consumer purchase behavior in social networks is shaped by a complex multi-layered system of risk perceptions that operate both directly and indirectly within the digital advertising environment.

The finding that security and privacy risks form one of the strongest drivers of consumer behavior is consistent with earlier studies showing that concerns related to data misuse, unauthorized access, and privacy violations are among the most influential determinants of online advertising evaluations. Previous research has demonstrated that privacy concerns significantly reduce consumers’ willingness to engage with commercial messages and contribute to avoidance behaviors, especially in personalized advertising contexts [3]. Similarly, interactions between consumers and brands on social media are highly sensitive to privacy vulnerabilities, with weak privacy protection decreasing consumer trust and engagement even when advertising content is appealing or relevant [5]. Our results align with this evidence, suggesting that unless privacy assurances are embedded into advertising practices, consumers perceive heightened risk and become reluctant to act on promotional messages. Furthermore, the influence of privacy and security risks is reinforced by literature emphasizing the "privacy paradox," where consumers express concern about privacy but simultaneously provide personal data under platform pressures [16]. Such contradictions highlight the complexity of privacy-related behaviors and support our finding that privacy risk occupies a foundational place in the hierarchy of advertising risks.

The role of product risk as a high-level influential factor is also strongly supported by prior literature. Studies show that when consumers encounter uncertainty regarding product authenticity, quality, or performance—particularly in environments lacking physical evaluation—they tend to adopt risk-averse behaviors [13]. Research on e-commerce and social media advertising similarly demonstrates that discrepancies between advertised messages and actual product performance contribute to distrust and undermine purchase intention [14]. Additionally, product-related ambiguity, counterfeit branding, or unclear product features can exacerbate perceived risk, especially in markets where product verification is challenging [7]. These findings collectively support our model's positioning of product risk as a principal driver influencing the overall risk structure and shaping downstream perceptions of functional, content-based, and operational risks.

Technology risk emerged as an equally significant driver, reflecting the increasing dependence of social media advertising on platform functionalities, content delivery algorithms, and the quality of multimedia formats. This result aligns with studies highlighting how technical glitches, poor interface usability, low-quality visuals, and outdated information reduce the credibility and persuasiveness of advertisements [11]. Furthermore, advancements in AI-driven personalization, algorithmic targeting, and automated content distribution introduce new forms of risk such as bias, misinformation, irrelevant targeting, or lack of transparency [19]. Research in digital advertising has also shown that users perceive advertisements as more credible when technological presentation is seamless, visually coherent, and contextually relevant [6]. The current study confirms these insights by identifying technology risk as a core structural variable that shapes both content-level perceptions and functional interpretations of advertisements.

The findings also revealed environmental risk as a highly influential factor, demonstrating that cultural, ethical, and regulatory considerations markedly shape consumer responses to social media advertising. This is consistent with studies arguing that advertising strategies must be culturally sensitive, ethically grounded, and aligned with contextual values to avoid triggering negative reactions [26]. Research confirms that advertisements perceived as culturally inappropriate, offensive, or inconsistent with local norms generate distrust and can substantially lower engagement or purchase intention [12]. Additionally, external environmental conditions—such as economic instability, social tensions, and regulatory enforcement—can magnify perceived risks by influencing how consumers interpret the intentions behind advertising content [23]. This supports our model's placement of environmental risk as a structural antecedent affecting the functioning of other risk types.

At the next hierarchical level, operational risk was identified as a linkage variable, meaning that it influences and is influenced by both higher-order and lower-order risks. This aligns with literature recognizing operational factors—such as response time, customer service reliability, ease of transactions, and return processes—as critical determinants of consumer trust in social media-based commerce [8]. Studies also show that prolonged exposure to promotional content, decision fatigue, and difficulties comparing alternatives contribute to consumer frustration, ultimately reducing their willingness to purchase through social networks [9]. The positioning of operational risk as a linkage factor confirms its dual nature: it is shaped by technological, product, and privacy risks but also shapes content and functional risk perceptions.

Content risk, placed at the mid-level in our model, is dependent on the reliability, clarity, and authenticity of the advertising message. Many studies illustrate that misleading advertisements, fake promotions, unverified influencer claims, and exaggerated content weaken consumer attitudes toward social media advertising [7, 29]. Research on influencer marketing further reveals that unclear sponsorship disclosure and manipulative messaging increase skepticism and reduce purchase intention [17]. Additionally, programmatic advertising has introduced concerns related to transparency, relevance, and algorithmic fairness, complicating how users interpret online advertisements [6]. These findings confirm the central role of content quality in shaping consumer perceptions, consistent with its intermediate placement in the structural model.

The study's results identified functional risk as a lower-level dependent factor, reflecting consumers' practical concerns about whether advertisements align with their needs and expectations. Previous literature suggests that functional misalignment—such as irrelevant targeting, lack of personalization, or insufficient informational value—reduces perceived usefulness and undermines decision confidence [19]. Scholars have also shown that functional risk contributes to emotional responses such as stress, confusion, and distrust when advertisements fail to meet informational or motivational needs [2]. These observations align with our finding that functional risk is strongly influenced by content, operational, and high-level risks but directly shapes the final outcome: behavioral purchase intention.

Finally, behavioral purchase intention appeared at the bottom of the model as the ultimate dependent construct. Prior studies confirm that purchase intention is the product of cumulative evaluations of trust, perceived risk, emotional response, and cognitive appraisal of advertisements [9, 18]. Research on e-commerce systems shows that purchase intention increases when consumers perceive advertisements as credible, secure, informative, and aligned with their personal needs [14]. Conversely, any elevation in perceived risk diminishes willingness to purchase, confirming the structural dependence identified in this study. The strong alignment between the structural model and prior literature reinforces the robustness of this hierarchical representation.

The MICMAC analysis further validated the structural relationships by demonstrating that environmental, technological, product, and security/privacy risks are independent drivers with high influence and low dependence. This finding aligns with interpretive structural modeling studies that identify contextual, technological, and regulatory variables as fundamental drivers shaping organizational and consumer systems [20, 27]. Similarly, the placement of operational risk in the linkage category is consistent with studies using total interpretive structural modeling (TISM) to analyze complex consumer behaviors and marketing determinants [22]. These methodological parallels provide additional support for the hierarchical model developed in this study.

Overall, the findings reveal that consumer purchase intention in social networks is influenced by a multi-dimensional risk structure, where high-level technological, environmental, product, and security/privacy risks initiate cascading effects across operational, content, and functional risks. This complex system highlights the need for integrated risk assessment approaches to improve advertising strategies across digital platforms.

This study, while comprehensive in its analytical approach, is limited by its sample size and reliance on expert judgment, which may restrict generalizability. The qualitative nature of the initial coding stage depends on subjective interpretations that may vary across experts or cultural contexts. Additionally, the ISM and MICMAC methods reveal structural relationships but do not measure statistical strengths, limiting quantitative validation. The study is also geographically bounded to specific regional market conditions, which may differ from global or cross-cultural environments.

Future studies should consider applying structural equation modeling or machine learning techniques to validate and predict the strength of relationships identified in the ISM model. Researchers may also explore longitudinal designs to examine how advertising risks evolve over time as social media platforms, consumer behaviors, and regulatory environments change. Expanding the study to include diverse markets and user demographics would enhance generalizability. Future studies could also integrate emotional, cognitive, and behavioral variables to develop more comprehensive predictive models of social media advertising effectiveness.

Practitioners should prioritize reducing high-level risks by strengthening privacy protection mechanisms, ensuring product authenticity, improving technological quality, and tailoring content to cultural norms. Advertising content must be transparent, accurate, and aligned with user needs to minimize functional and content-related risks. Companies should streamline operational processes such as customer service responsiveness, return policies, and information clarity to enhance consumer confidence. Overall, mitigating these layered risks will help brands improve purchase intention and consumer trust in social media environments.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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