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Providing an Analytical Model of the Relationship Between Advertising Content Risks and Behavioral Intention in Social Networks

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A B S T R A C T

Objective: The objective of this study is to examine how various risks affect consumers' reactions and purchase intentions in social media advertising.

Methodology: The research employed a mixed-method approach. Initially, Interpretive Structural Modeling (ISM) was used to identify relationships between risks, followed by Structural Equation Modeling (SEM) using SMART PLS to test these relationships quantitatively. Data were collected through a cross-sectional survey of social media users, and the relationships between identified risks were analyzed.

Findings: The results show that "environmental risk," "technology risk," "product risk," and "security and privacy risk" influence "operational risk." Moreover, operational risk positively affects "content risk," which in turn influences "functional risk." "Functional risk" negatively impacts consumers' behavioral intentions to purchase, while content risk undermines the credibility of ads, diminishing their perceived functionality and value. Findings support the theoretical literature on risks in online advertising and consumer behavior.

Conclusion: The study concludes that managing advertising risks, particularly content, functional, and operational risks, is crucial for enhancing consumer trust and purchase intentions. Marketers should focus on transparent ad content, secure payment systems, and addressing product information risks to mitigate the impact of these risks. Future research should explore additional variables, such as trust and commitment, to provide a more comprehensive understanding of risk perceptions in social media advertising.

Keywords: *Advertising, Social Networks, Advertising Risks.*

1 Introduction

Social networks have strengthened communication, sharing, and collaboration among users, providing attractive opportunities for interaction between consumers and marketing managers (Wiese & Akareem, 2020). With the emergence of this potential, organizations' interest in advertising through this medium has increased (Tuten & Mintu-Wimsatt, 2018). Consequently, setting advertising objectives in social networks has become an essential subject in strategic planning (Bulut & Özcan, 2023). Moreover, social media provides vast and rapid information (Sohaib et al., 2018), and the quick circulation of information leads to the dissemination of incomplete and fake information (Genç & Turna, 2023), which can be risky (Sohaib et al., 2018) and create concerns for consumers (Brough & Martin, 2021). These concerns regarding advertisements can influence consumer attitudes toward ads and their purchase intention (Lin & Kim, 2016). Researchers have found that some online advertisements overstate the product's appeal, provide ineffective or incorrect information, excessively collect and use users' private data, waste their time, and limit their freedom of search and choice, thus creating negative behaviors and attitudes (Matiza & Kruger, 2021; Sharma et al., 2021). Wang et al. (2022) demonstrated that a lack of targeted advertising, such as perceived cost, privacy issues, ad clutter, misunderstood objectives, authenticity of advertisements, weak interaction and communication in ads, platform credibility, ad confusion, perceived convenience, and lack of integration, causes consumers to avoid advertisements (Wang et al., 2022). It has been stated that in social media advertising, if customers feel that the information is inaccurate, it will likely have a negative impact on their purchase decisions (Palla et al., 2013). When consumers perceive that the advertisement for a product or service does not meet their minimum requirements, they tend to perceive risks and adopt avoidance behaviors to reduce exposure to such risks, resulting in increased advertising costs without improving revenues, threatening the survival of organizations (Wang et al., 2022).

Online shopping, due to the physical distance between buyer and seller, creates uncertainty. Therefore, the risk factor arises (Kim et al., 2012). According to Federman and Pavlou (2003), risk in social media includes various forms of dangers, such as exposure to personal information, source risk, psychological risk, and more (Sohaib et al., 2018). When perceived risk increases, users are likely to avoid sharing information and participating in e-commerce, but if protective measures are implemented, consumers are more likely to respond positively to advertisements (Alkis & Kose, 2022). In other words, people are more likely to engage in interactions when they trust and find the advertisement useful (Dwivedi et al., 2019). The results indicate that social media-related features, such as reducing perceived risk and enhancing consumer trust, influence their purchase intention in such virtual contexts (Farzin et al., 2022). According to Martin's (2018) study, online trust reduces perceived risk, and an increase in trust is likely to reduce purchase risk (Martin, 2018).

Empirical research has not yet fully demonstrated which social media advertising concerns are significant deterrents for marketers (Lin & Kim, 2016). Therefore, cognitive evaluation of risks and threats is essential for anticipating future outcomes (Bright et al., 2022). Online companies must understand risk and develop appropriate strategies to mitigate perceived risk in online purchases (Kim et al., 2009), encouraging customers to make purchasing decisions on social media (Wang et al., 2022). Additionally, with the increase in digital users, especially during the COVID-19 pandemic, business activities and advertising on digital platforms, such as social media, have grown, leading to an increase in risks and frauds, which can negatively impact consumer purchase intention and ultimately raise the risk for digital businesses. Despite the studies conducted by academics and professionals on online environment risks, the theoretical literature remains unclear on the risks consumers face in advertising content, and there is limited information on how these risks affect consumer purchase intention in both domestic and international theoretical literature. Moreover, increasing consumer concerns about disruptive advertisements poses challenges for marketing managers in strategic marketing planning and setting advertising objectives in social media. To reduce this research gap and resolve the issue, we have posed the following questions, which this study aims to answer:

- What are the content risks of advertising and behavioral intention in social networks?
- What are the relationships between advertising content risks and behavioral intention in social networks?
- What is the structural model of advertising content risks and behavioral intention in social networks?
- Is the analytical model of the relationship between advertising content risks and behavioral intention in social networks valid?

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2 Methods and Materials

The present study, aimed at providing an analytical model of the relationship between advertising content risks and behavioral intention in social networks, was conducted in two qualitative and quantitative phases. This research, in terms of purpose, is developmental-applied, and in terms of nature and method, it is descriptive-exploratory. The statistical population in the qualitative section includes 30 social media marketing managers, as well as professors and researchers in the field of marketing, selected through purposive non-probability sampling and the snowball technique. The selected participants had higher education, extensive experience, and were accessible. The sample size was determined based on theoretical saturation, where codes were repeated. In the quantitative section, the statistical population consisted of social media users in Tehran, with a sample of 391 randomly selected cluster samples from five regions of Tehran.

Since the indicators and codes for the research model were not initially clear, and to localize the risks, content analysis was used in the qualitative phase. Qualitative content analysis systematically presents a set of texts and uses a fixed coding framework to record and classify explicit and implicit content. Qualitative content analysis adopts a realist epistemology. In the qualitative section, a semi-structured interview was conducted with experts, and they were asked to list the risks. The key points extracted from the interviews were categorized and classified through open, axial, and selective coding, using a deductive and inductive approach, and the advertising content risks that may play a role in consumer behavioral intention were identified. In the inductive approach, the codes were extracted from interviews, and in the deductive approach, selective and axial codes were identified through theoretical literature. Finally, the identified codes were evaluated and validated using the fuzzy Delphi method. The fuzzy Delphi method is applied to gather consensus from an expert panel regarding criteria, and their uncertain opinions are examined using a set of fuzzy numbers. For validity, sufficient evidence and documentation were provided, and the variables' formation was validated by consulting specialists. For reliability, the fuzzy Delphi method was used to confirm the acceptability of the findings. For transferability, interviews were conducted in different locations and times.

In the quantitative section, using the Interpretive Structural Modeling (ISM) technique, based on expert opinions, the relationships between risks were identified, determined, and a conceptual model was designed. In ISM, the variables of the theoretical model are examined on a structural basis, the relationships between these variables are determined, and ultimately, it shows how variables influence each other to uncover the impact of one variable on another (Bakhtari et al., 2020). ISM can transform vague thoughts and perspectives into visual models with well-defined structural relationships, which is useful for systems with complex relationships and unclear structures (Lin et al., 2019). Therefore, since the relationships and effects between advertising content risks and behavioral intention in social networks are unclear in the theoretical literature, and given the capability of ISM to determine these relationships, we used this method to present a structural model and how these factors influence each other.

Finally, the designed model was validated using Structural Equation Modeling (SEM) and the partial least squares (PLS) technique, based on the opinions of social media users. SEM provides the relationships between variables and the quality criteria for construct formation with correlation coefficients.

3 Findings and Results

To identify the risks, semi-structured interviews were conducted with experts. After organizing all the notes, open coding based on an inductive approach (interview assistance) was performed. Then, with the help of the esteemed supervisors and advisors, the codes were reviewed to ensure their reliability. Subsequently, the initial codes were grouped deductively (with the help of theoretical literature) and categorized into several higher-level categories based on similarities and differences between the codes. Depending on the relationships between the categories (in axial coding), they were combined into meaningful clusters of core concepts (selective coding). After completing the coding and categorization process, a hierarchical structure consisting of concepts, categories, and open codes was established. The analysis concluded by developing definitions for each concept (main risks) and category (sub-risks). The fuzzy Delphi method was employed to reach a consensus on the importance of risks in the study. The experts determined the significance of each identified risk. The fuzzy Delphi method was conducted in three rounds. In the second round, the experts provided feedback on eliminating, modifying, merging, or adding new codes, and these opinions were compared with the first round. The decision-making principle in Delphi was based

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on Karimi Shirazi et al. (2017) and the Pareto rule of 80/20. If the level of disagreement in the first and second rounds was less than the threshold of 0.2, the survey was stopped; however, for variables with a difference greater than 0.2, a third round of the fuzzy Delphi survey was conducted. Codes with an average expert score greater than 8 were selected, and those below 8 were removed. Therefore, the result of the fuzzy Delphi method indicated 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 advertising content risks and behavioral intention in social networks. These risks serve as inputs for the Interpretive Structural Modeling (ISM) method to determine the relationships between them.

Table 1

Advertising Content Risks 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 – Use of my information history by others
	Security Risk	Threat to asset security – Insecurity of my information – Unsafe purchasing
Product Risk	Product/Service Offering Risk	Risk of only providing information without service/product offering – Incomplete information about product/service quality – Risk of after-sales service
	Product Trust Risk	Risk of product not matching my perception – Risk of trusting product according to ad content – Unclear product features
	Product Brand Risk	Risk of counterfeit trademark – Risk of negative brand interaction or feelings – Unreliable brands
Content Risk	Credibility Risk	Hacking of ad content – Unrealistic and fake ad interactions – Risk of fake messages – Quick removal of ad content
	Agency Relationship Risk	No commercial connection with ad content – Unidentifiable commercial connection in ad content – Risk of no link between content and sellers
	Ad Capability Risk	Projection and diffusion of ad content – Risk of influencers not understanding product quality – Risk of too much confusing content
Technology Risk	Clarity Risk	Non-conformity of designs and formats – Risk of ad content quality (text, video, and images)
	Information Risk	Risk of incorrect or outdated data – Dissemination of false or misleading information – Low-quality and weak information
Environmental Risk	Social Risk	Cultural ridicule in social networks – Cultural conflict in social networks – Promotion of violence in social networks – Destructive behaviors in ad 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 from incentives (price – discount) – Risk of unanswered questions – Risk of returning or exchanging goods – Cost risks
	Perceived Time Loss Risk	Excessive time spent reviewing ad content – Excessive time comparing ads and decision-making – Irrelevant ad timing
Functional Risk	Perceived Usefulness Risk	Straying from the goal – Challenge in purchasing – Customization of consumer needs not achieved
	Ambiguity Risk	Risk of emotional manipulation – Risk of stress and anxiety – Feeling insecure in purchasing
	Perceived Value Risk	Risk of poor impact on decision-making – Risk of interference in selection
	Relevance Risk	Ads not aligned with my needs – Ads not aligned with expectations – Risk of not matching informational needs
Behavioral Purchase Intention	Purchase Intention	Using social networks for purchasing – Purchasing products/services – Willingness to purchase

The main risks of social media advertising content, presented in Table 1, were selected for ISM modeling. The first step in ISM is determining the structural matrix of internal relationships. To collect data, a paired comparison questionnaire was designed, and the experts rated the impact of each risk on the others as no impact (0), low impact (1), moderate impact (2), and high impact (3). The aggregate responses of 30 experts were calculated, and the structural matrix of internal relationships was obtained. Subsequently, the structural self-interaction matrix was converted into a binary (zero and one) matrix known as the initial reachability matrix. In the third step, the reachability matrix was adjusted for consistency. In the adjusted reachability matrix, indirect relationships between risks are uncovered. The consistency principle is such that if factor A affects B (1), and B affects C (1), then necessarily C affects A (1). These calculations were performed using MS Excel and Boolean logic, and the adjusted reachability matrix was formed. The results are presented in Table 2.

Table 2

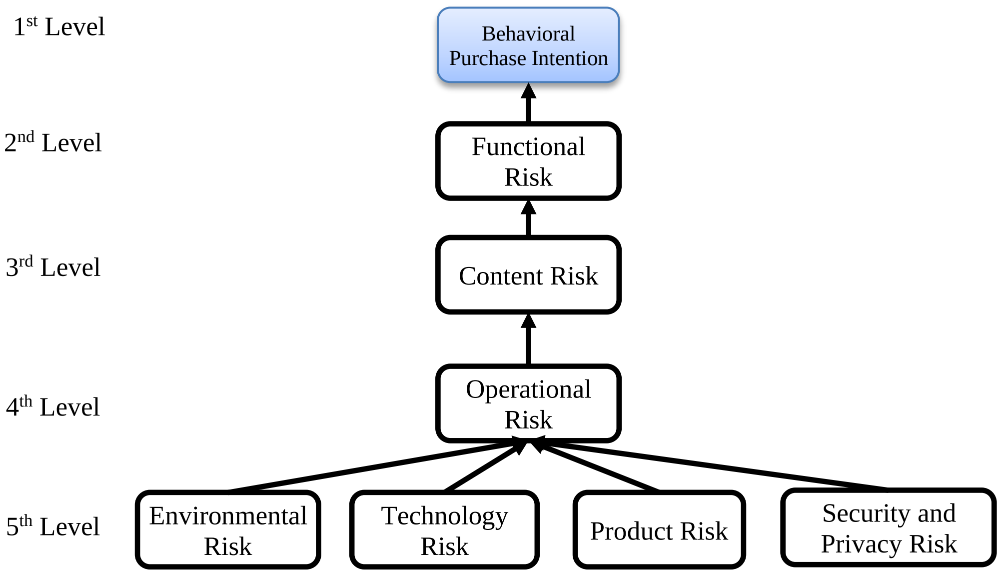
Adjusted Reachability Matrix

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

In the fourth step, to partition the risks and create the structural model, we calculated the driving power and dependence of each risk in the adjusted reachability matrix. These calculations are shown in Table 2. The net influence/dependence power for each risk was determined, and the risks were ranked in descending order. The dependent risks were placed at the first levels, while the influential risks were placed at higher levels in the model. Risks with equal influence/dependence were placed on the same level. In the fifth step, after determining the relationships and risk levels, they were visually represented as a structural model shown in Figure 1.

Figure 1

Interpretive Structural Model of Advertising Content Risks and Behavioral Intention in Social Networks



As shown in Figure 1, the advertising content risks and behavioral intention in social networks are classified into five levels. At the fifth level, "Environmental Risk," "Technology Risk," "Product Risk," and "Security and Privacy Risk" are placed, which have the most significant impact on behavioral intention in social networks. These

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risks are not interconnected but affect the next level. At the fourth level, "Operational Risk" is placed, which influences the third level, "Content Risk." At the second level, "Functional Risk" is situated, which is influenced but impacts the first level. At the first level, "Behavioral Purchase Intention" is positioned, which results from the consumer's perception of advertising content risks in social networks.

We use the statistical technique of Structural Equation Modeling (SEM) to measure and analyze the relationships between observed and latent variables in the interpretive structural model. To this end, data from 391 customers were collected using a Likert-scale questionnaire. The skewness and kurtosis observed for the model variables fell outside the range of (-1, 1), indicating that the variables do not follow a normal distribution. Therefore, the data can be analyzed using SMART PLS software.

The measurement model was constructed to assess the quality of the latent variables' data. Confirmatory factor analysis was used to evaluate the reliability and validity of the latent variables in the model. To confirm construct validity, the average variance extracted (AVE) score must be greater than 0.5. The Fornell-Larcker criterion was used to assess discriminant validity by determining whether the square root of the average variance extracted is greater than the correlation between the latent variables. For reliability, factor loadings greater than 0.5 for each observed variable were considered acceptable, with values above 0.7 being excellent. Composite reliability (CR) and Cronbach's alpha were used to assess the reliability of the latent constructs, with values above 0.7 being required. Table 3 shows the items used for each construct, Cronbach's alpha values, composite reliability, and AVE scores.

Table 3

Measurement Model: Factor Loadings, Reliability, and Convergent Validity

Variable (Indicators)	Average Variance Extracted (AVE)	Factor Loading	t-Values	P-value	Cronbach's Alpha	Composite Reliability (CR)
Security and Privacy Risk	0.600	0.771	9.262	0.000	0.891	0.912
Q2		0.867	22.167	0.000		
Q3		0.846	18.186	0.000		
Q4		0.797	15.934	0.000		
Q5		0.699	7.461	0.000		
Q6		0.688	7.625	0.000		
Q7		0.735	9.614	0.000		
Product Risk	0.626	0.689	9.915	0.000	0.929	0.937
Q9		0.806	10.403	0.000		
Q10		0.797	9.587	0.000		
Q11		0.872	12.581	0.000		
Q12		0.824	11.783	0.000		
Q13		0.824	12.420	0.000		
Q14		0.822	11.574	0.000		
Q15		0.653	9.691	0.000		
Q16		0.810	22.367	0.000		
Content Risk	0.599	0.796	9.651	0.000	0.923	0.936
Q18		0.910	20.272	0.000		
Q19		0.712	7.311	0.000		
Q20		0.773	10.001	0.000		
Q21		0.832	10.700	0.000		
Q22		0.549	4.822	0.000		
Q23		0.642	4.769	0.000		
Q24		0.838	17.544	0.000		
Q25		0.834	17.920	0.000		
Q26		0.789	13.441	0.000		
Technology Risk	0.566	0.808	10.932	0.000	0.825	0.867
Q28		0.743	11.031	0.000		
Q29		0.760	7.176	0.000		
Q30		0.712	5.939	0.000		
Q31		0.736	6.227	0.000		
Environmental Risk	0.665	0.653	5.903	0.000	0.900	0.922
Q33		0.839	4.960	0.000		

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Q34		0.840	4.886	0.000		
Q35		0.867	8.316	0.000		
Q36		0.821	6.033	0.000		
Q37		0.853	9.626	0.000		
Operational Risk	0.571	0.749	11.645	0.000	0.879	0.903
Q39		0.738	9.206	0.000		
Q40		0.702	7.878	0.000		
Q41		0.716	8.475	0.000		
Q42		0.807	15.922	0.000		
Q43		0.799	16.157	0.000		
Q44		0.771	13.688	0.000		
Functional Risk	0.625	0.796	14.263	0.000	0.939	0.948
Q46		0.814	13.077	0.000		
Q47		0.735	9.197	0.000		
Q48		0.777	9.526	0.000		
Q49		0.834	21.635	0.000		
Q50		0.816	16.030	0.000		
Q51		0.886	20.869	0.000		
Q52		0.764	9.373	0.000		
Q53		0.887	23.356	0.000		
Q54		0.623	4.796	0.000		
Q55		0.724	8.184	0.000		
Behavioral Purchase Intention	0.818	0.860	19.570	0.000	0.888	0.931
Q57		0.943	47.937	0.000		
Q58		0.909	35.342	0.000		

The minimum factor loading for the indicators used for each construct is 0.549, which is greater than 0.5 and significant. The minimum Cronbach's alpha value is 0.825. The composite reliability score has a minimum value of 0.867, and the AVE score has a minimum value of 0.566, indicating that the variables have good reliability and validity.

Table 4

Correlation Coefficients and Discriminant Validity among Research Variables

	Operational Risk	Behavioral Purchase Intention	Security and Privacy Risk	Technology Risk	Content Risk	Product Risk	Environmental Risk	Functional Risk
Operational Risk	0.756							
Behavioral Purchase Intention	-0.764	0.904						
Security and Privacy Risk	0.775	-0.736	0.774					
Technology Risk	0.629	-0.682	0.536	0.752				
Content Risk	0.738	-0.778	0.702	0.609	0.774			
Product Risk	0.752	-0.579	0.676	0.580	0.786	0.791		
Environmental Risk	0.321	-0.231	0.330	0.651	0.190	0.363	0.815	
Functional Risk	0.771	-0.800	0.773	0.670	0.708	0.755	0.371	0.790

It is observed that the square root of the average variance extracted from the six latent variables is greater than the correlation between the latent variables, indicating that the data do not have validity issues. Therefore, the collected data in this study is suitable for further analysis. Overall, the measurement characteristics of the constructs used in our analysis are sufficient, allowing us to evaluate the structural model results. The t-statistic and bootstrapped p-values for assessing the significance of the relationships at a 5% error level are shown in the following.

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Table 5

Results of Structural Equations and Relationship Testing

Relationship	Independent Variables	Dependent Variables	Q^2	R^2	Beta	t	Relationship Direction	Result
1	Security and Privacy Risk	Operational Risk	0.421	0.837	0.631	8.118	+	Confirmed
2	Product Risk	Operational Risk	-	-	0.234	3.748	+	Confirmed
3	Technology Risk	Operational Risk	-	-	0.238	2.949	+	Confirmed
4	Environmental Risk	Operational Risk	-	-	-0.127	1.612	-	Rejected
5	Operational Risk	Content Risk	0.370	0.702	0.838	23.244	+	Confirmed
6	Operational Risk	Functional Risk	0.491	0.873	0.401	4.996	+	Confirmed
7	Content Risk	Functional Risk	-	-	0.572	6.932	+	Confirmed
8	Functional Risk	Behavioral Purchase Intention	0.488	0.640	-0.800	11.810	-	Confirmed

Figure 2

Structural Model Confirmatory Factor Analysis and Path Coefficients

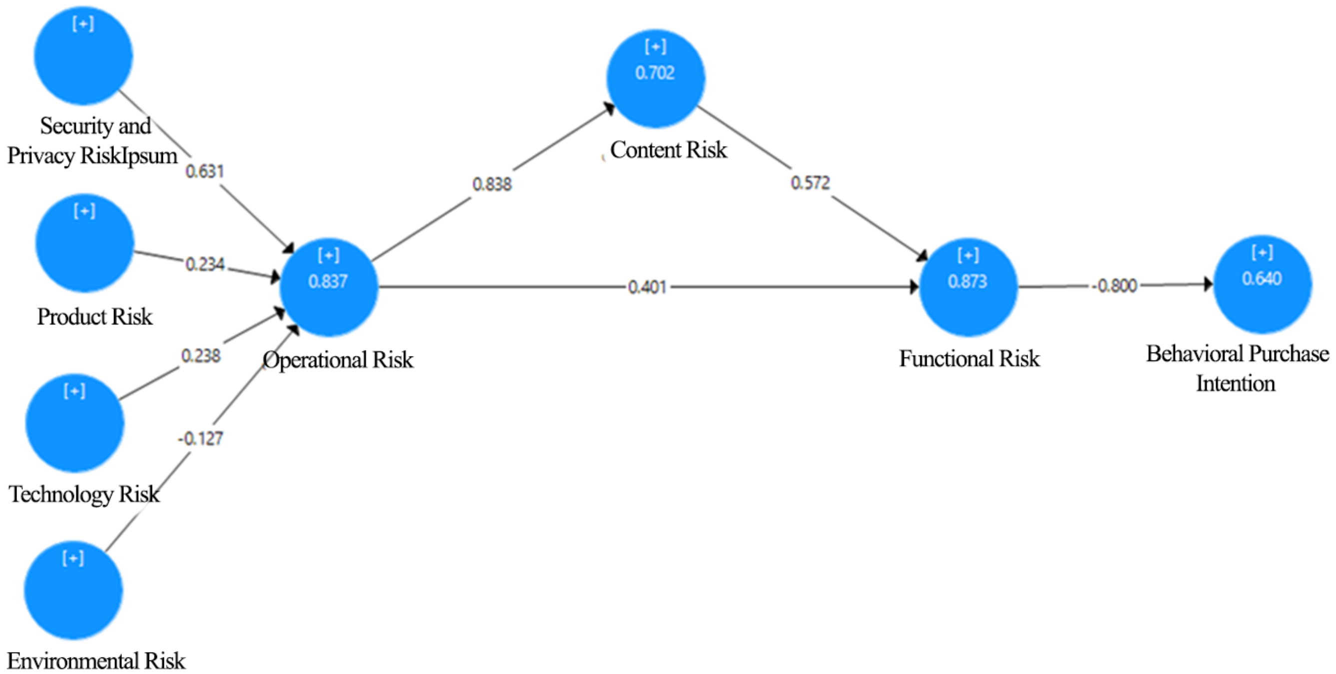

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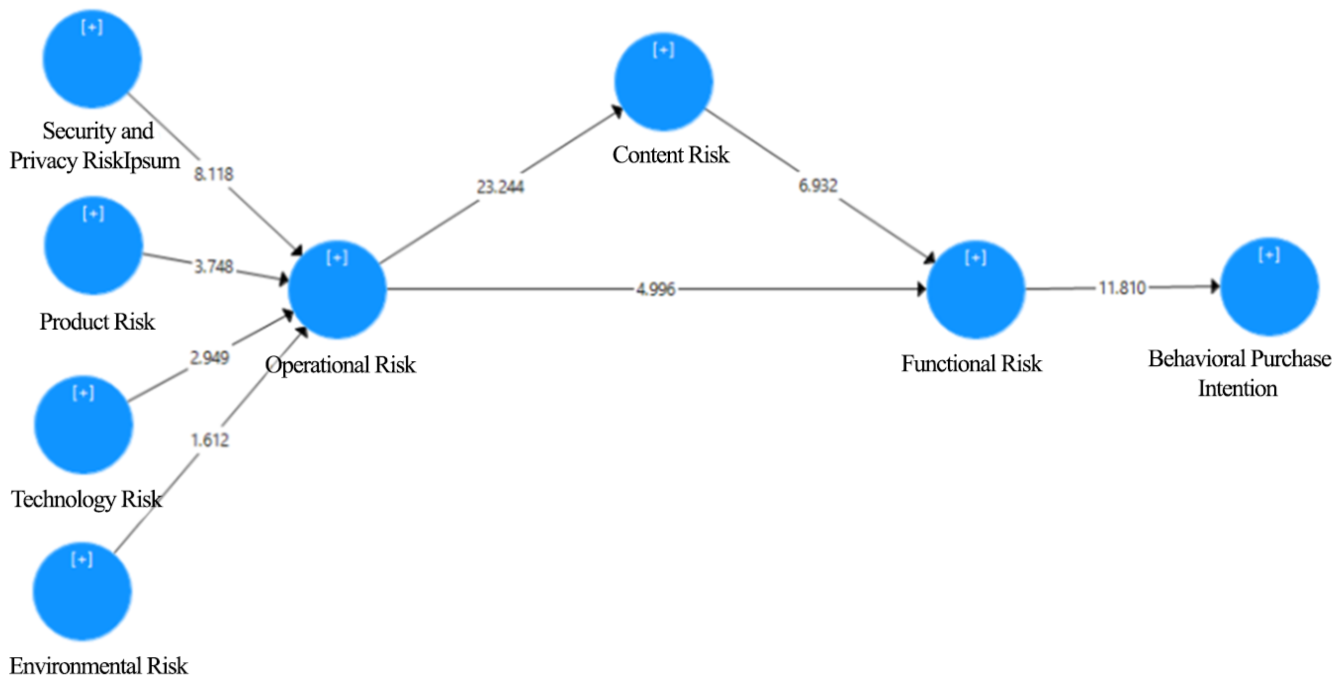
Figure 3

Structural Model Significance (T-Values)



The R^2 values of the latent variables in the model, which indicate the percentage of the independent variable's changes explained by the dependent variable, were obtained. The findings show that over 64% of the changes in the dependent variables are explained by the independent variables, which is a strong predictive percentage. To evaluate the predictive relevance of the model, we used the Q^2 criterion. The PLS results show that the latent variables have more than 37% predictive ability for the dependent variables, which is an acceptable value. Finally, to further ensure the overall quality of the measurement and structural model, we used the GOF criterion with the formula GOF=√((AVE)̅×(R^2)̅). The higher this index, the better the model fit.

Based on the findings, the GOF criterion value is 0.683, and since the obtained GOF is greater than 0.36, the overall fit of the model is strong. Therefore, given the evaluation and confirmation of the structural model, we can trust and interpret the relationships between variables.

The first relationship shows a significant positive effect between "Security and Privacy Risk" and "Operational Risk" (β=0.631, t=8.118). The second relationship shows a significant positive effect of "Product Risk" on "Operational Risk" (β=0.234, t=3.748). In the third relationship, the effect of "Technology Risk" on "Operational Risk" is confirmed, given the significance of the statistic (t=2.949). The fourth relationship depicts the non-significance of the effect of "Environmental Risk" on "Operational Risk" (β=-0.127, t=1.612). The fifth relationship confirms the effect of "Operational Risk" on "Content Risk" based on the significant statistic (t=23.244). The sixth relationship shows a significant positive effect of "Operational Risk" on "Functional Risk" (β=0.401, t=4.996). The seventh relationship confirms the significant effect between "Content Risk" and "Functional Risk" based on the significant statistic (t=6.932). The eighth relationship shows that based on the data, "Functional Risk" has a significant negative effect on "Behavioral Purchase Intention" (β=-0.800, t=11.810).

4 Discussion and Conclusion

Our study demonstrates how "functional risk," "content risk," "operational risk," "security and privacy risk," "product risk," "technology risk," and "environmental risk" can trigger adverse consumer reactions. Thus, consumers' acceptance and use of social media advertisements are influenced by concerns that are decisive in shaping their purchase intentions. Given the research findings and the identification of risks, the novelty of our study lies in highlighting "content risk," "functional risk," and "environmental risk," which, due to the unidentifiable commercial connection in ad content and the presence of unrealistic and fake advertisements, can significantly affect consumers. Additionally, the lack of clarity regarding

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adherence to rules and regulations by digital sellers can lead to behaviors in advertising that unintentionally attract users, although these behaviors may be harmful. From a managerial perspective, this study suggests that marketers should focus their attention on managing advertising risks within social media platforms. The findings of our study are supported by existing literature. For instance, Aiolfi et al. (2021) emphasize privacy risks in advertising content, Masoud et al. (2013) focus on product risk in online environments, Taro et al. (2021) on technology risk, and Muneekrishnan et al. (2023) highlight the impact of risks on purchase intent within platforms (Aiolfi et al., 2021; Masoud, 2013; Munikrishnan et al., 2023). Considering these studies and our research findings, the importance of content risks in advertising emerges as a crucial prerequisite for content creation.

In the quantitative section, the relationships between risks were identified using Interpretive Structural Modeling (ISM), and a structural model was formed. Subsequently, the relationships in the generated model were tested using Structural Equation Modeling (SEM) and SMART PLS. The findings revealed that in the ISM, "environmental risk," "technology risk," "product risk," and "security and privacy risk" influence "operational risk." Therefore, to increase sales and motivate users to purchase, the priority is to manage and control these four risks. The analysis of relationships using SEM shows that except for "environmental risk," the other risks have a significant positive effect on "operational risk." This finding indicates that the risk related to advertising content quality and destructive behaviors by sellers increases the operational risk of purchasing, ultimately leading to customer avoidance of purchase. According to Yeoh et al. (2020), unreliable, incorrect, and insufficient information can reduce the trust of online customers. Users who cannot physically see or touch the product face purchasing challenges. Thamizhvanan and Xavier (2013) suggest that the insecurity of e-commerce transactions can increase transaction risk (Thamizhvanan & Xavier, 2013). To reduce these risks, it is recommended that social media store managers create secure payment gateways for users, focus on the quality of images, videos, and graphics to reduce technology risk, and provide product information, including features and quality, in ad content to lower the risk of product fraud. To reduce environmental risk, brands are advised to comply with legal boundaries and avoid violating social contracts.

The findings also show that "operational risk" has a significant positive effect on "content risk" in both ISM and SEM. This indicates that operational risk in social media ad content, through the creation of false excitement about a product's features, can impact content risk. Based on Masoud (2013), financial loss from either monetary fraud or dissatisfaction with the purchased product can affect trust in online shopping (Masoud, 2013). Moreover, Arifin et al. (2018) suggest that perceived time risk and risks related to unmet product expectations increase customer credibility risk and expectations (Ariffin et al., 2018). It is recommended that marketing managers reduce operational risk and content risk by offering online price comparisons with competitors, ensuring product authenticity, timing ads appropriately, and managing the number of ad contents.

"Content risk" influences "functional risk," as supported by SEM findings in a positive and significant manner. Content risk affects functional risk through a lack of credibility. When users suspect the authenticity of ad content, the credibility of the content decreases, resulting in the diminished perceived functionality and value of the product or service for users. Consequently, users perceive the ad content as irrelevant to their needs and avoid purchasing. Managers can help reduce content risk by ensuring transparency in ad text, clarifying commercial connections between influencers or celebrities and brands, and selecting appropriate timing for advertisements.

In the ISM, "functional risk" affects "behavioral intention," and this relationship is confirmed to be negative and significant in SEM. This finding suggests that functional risk creates ambiguity for users, leading to negative behavioral intentions and causing them to abandon purchases. The findings of Ammarullah (2023) show that perceived risk negatively affects e-commerce purchase intention (Amarullah, 2023). Similarly, the findings of Muneekrishnan et al. (2023) support our results, demonstrating that time risk and psychological risk in online stores significantly influence online purchase intentions (Munikrishnan et al., 2023). Zhao et al. (2017) also show that purchasing behavior is influenced by perceived risk related to product quality and monetary loss during purchases (Zhao et al., 2017). To increase consumer purchase intentions, it is recommended that ad content be created based on research, utilizing analysis, listening to feedback, and segmenting audiences according to their characteristics and behaviors.

Finally, as a limitation, this study utilized a cross-sectional survey for data collection, and the generalization of these findings should be done with caution in terms of time. Additionally, this research may have overlooked other variables and risks that influence behavioral intention

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outcomes. Given the study's limitations, future researchers are encouraged to explore this topic with different populations and consider including moderating variables, such as commitment or trust, between social media risks and purchase intention. Furthermore, future models should examine respondents' personal characteristics, such as their previous shopping experience, in relation to their risk perception and purchase behavior intention.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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