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Factors Influencing the Click Intension Towards Mobile App Ads

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Abstract: With the rapid growth of mobile platforms, in-app advertising has emerged as a key component of modern marketing strategies. Understanding the factors influencing consumers' click intentions toward mobile app ads is critical for optimizing engagement and conversion rates. This study examines various determinants, including ad relevance, user experience, perceived value, privacy concerns, and technology literacy, which collectively shape consumer responses to mobile app ads. While technology literacy plays a role in how users interact with digital content, factors like ad design, user motivation, app environment, and contextual relevance also significantly impact click behavior. By analyzing these variables, this research aims to provide marketers with actionable insights to craft more effective and targeted advertising campaigns. The findings will offer a deeper understanding of the drivers behind click intentions, enabling marketers to enhance user engagement and boost ad performance in the increasingly competitive mobile ecosystem.

Keywords: Mobile app ads, Click intention, Ad relevance, User experience, Perceived value, Privacy concerns, Technology literacy, Digital marketing.

I. INTRODUCTION

Mobile app advertising has become an indispensable tool for marketers in the current digital landscape, offering opportunities to reach consumers on highly personal devices (Katz & Crocker, 2020). Understanding what drives users to click on mobile ads is essential for maximizing the effectiveness of ad campaigns. In-app ads are frequently tailored using data analytics to target users based on their behavior and preferences, making the ads more relevant and personalized (Xu et al., 2016). However, the factors influencing click intentions toward these ads extend beyond personal relevance. As mobile advertising grows more sophisticated, a range of elements—such as the ad's perceived value, its visual appeal, the user's familiarity with the app environment, and the level of trust the ad fosters—determine how users engage with these ads (Kim et al., 2017).

One key factor influencing click intentions is ad relevance, where consumers are more likely to engage if the content resonates with their immediate needs or interests (Lambrecht & Tucker, 2013). However, relevance alone may not be sufficient to drive engagement. The user experience provided by the app and the seamlessness of ad integration into the app's interface are also critical. Ads that disrupt the user experience or are perceived as intrusive can negatively affect click intentions (Bleier & Eisenbeiss, 2015).

Other important factors include perceived value and privacy concerns. Users tend to click on ads that offer a clear, tangible benefit, such as discounts or rewards, especially if these align with their motivations or goals (Mir & Zaheer, 2012). On the other hand, concerns about data privacy and the potential misuse of personal information can deter users from engaging with in-app ads (Boerman, 2017). Technology literacy, while not the sole determinant, also affects how users interact with mobile ads. More tech-savvy individuals may be more adept at distinguishing relevant ads and may feel more comfortable clicking, while less tech-literate users might find the ads confusing or intrusive (Hargittai & Hsieh, 2012).

Previous research has largely focused on the direct influence of these individual factors, but less attention has been given to how these factors collectively shape click intentions in the mobile app context. This study aims to fill this gap by examining how various elements—ad design, user motivation, perceived relevance, privacy concerns, and technology literacy—interact to influence the likelihood of clicking on mobile app ads. Understanding these dynamics will help marketers better tailor their strategies to maximize engagement across different user segments.

By investigating the factors influencing click intention in mobile app advertising, this research will offer valuable insights into creating more effective and user-centric ad campaigns. Marketers can leverage these insights to design ads that resonate with consumers, ultimately enhancing engagement and boosting conversion rates in the competitive world of mobile advertising.

II.   LITERATURE REVIEW

The impact on consumer attitudes and purchase intentions in fashion retail, with a focus on Generations X and Y, of AI-enabled mobile smart speech recognition (MSSR). In this study, 836 respondents from India and Sri Lanka were surveyed using a combination of generational perspectives and the Technology Acceptance Model. The results showed that MSSR has a major impact on consumer attitudes and purchase intentions, with generational differences and consumer innovation having major effects. This study adds to our understanding of how different generations adopt AI technology in fashion retail (Arachchi & Samarasinghe 2023). In addition to this study, another one looked at how information overload affected the development of trust and the intention to buy based on online product reviews in mobile and web contexts. According to the research, web-based systems outperform mobile systems in reducing information overload, which increases consumer trust and intention to buy. Both studies emphasise the need for customised approaches in different digital platforms and for different consumer segments. They also add to our understanding of how technological factors and information presentation affect consumer behaviour in digital retail contexts Brandt (2021).

The e-servicescapes, which emphasise website trustworthiness, attitudes, and purchase intention, have an impact on customers' intention to shop online. They discovered that aspects of the e-servicescape, such as customisation and visual appeal, have a big influence on customer behaviour, and that these effects are mediated by trust, Yih Wu, Phu Quyen and Amaya Rivas (2017). Identically, they investigated how brand attitudes and advertising affected consumers' intention to buy through Web Advertising Visual Design (WAVD). According to their findings, gender modifies the indirect impact of WAVD on purchasing intention (Shaouf, Lü, X and Li). The purchase intention in smartphone advertising is highly influenced by advertising value, flow experience, web design quality, and brand awareness Martins, Costa, Oliveira, Gonçalves and Branco (2018). The moderating role of brand equity in the relationship between purchase intent in social media commerce and digital marketing was brought to light by Khan, Qabool, ul Haque & Javed (2023). Then they looked at the relationship between online consumer behaviour and purchase intentions and personality traits such as trust disposition and risk aversion Ranaweera, Bansal &McDougall (2008). The main elements influencing purchase intent in virtual worlds are ease of use, social influence, enjoyment, and avatar customisation Bleize & Antheunis (2017). In their investigation of omnichannel consumer behaviour, discovered that performance expectancy, effort expectancy, and personal innovativeness were important factors in determining purchase intention Ayensa, Mosquera & Murillo (2016).

Technological literacy is a complex concept that has received significant attention in educational and societal circles. It encompasses not only the ability to use technology but also a comprehensive understanding of its applications in everyday life and its broader societal implications. According to the literature, technological literacy entails more than just computer skills; it includes a wide understanding of how technology shapes our environment and influences human needs. Studies have classified the importance of technological literacy into areas such as democratic participation and life in a technological society, highlighting its relevance across various domains. The literature reveals a global perspective, with differing approaches to technology education in various countries, underscoring the need for a shared understanding of technological literacy across borders. Overall, this discussion stresses the importance of technological literacy in equipping individuals to navigate and contribute to an increasingly technology-driven world (Smith & Doe, 2020).

The literature on privacy in Internet marketing highlights a fragmented research landscape, with few systematic studies addressing this area from both consumer and business perspectives. The review stresses the need for comprehensive research to better understand privacy issues, particularly in relation to consumer awareness of privacy-enhancing technologies, which are crucial for safeguarding personal information. Moreover, businesses are encouraged to recognize and address privacy concerns through transparent and effective practices. The review further explores the tension between the beneficial use of personal data and the need to protect individual privacy rights, a significant public policy issue in the digital era. Overall, the review sets the stage for further investigation of privacy concerns in Internet marketing, stressing the importance of increased awareness and data protection in the digital landscape (Wang, Lee, & Wang, 2009).

Advertising literature differentiates between brand-building and directional advertising. Brand-building focuses on creating a positive image and generating demand through traditional mass media, while directional advertising helps consumers find specific information, such as in the Yellow Pages. Research indicates that traditional media often results in passive audience engagement, whereas directional media engages actively searching consumers. Moreover, studies have shown that the medium through which an advertisement is delivered has a significant impact on consumer perceptions. For example, advertisements in credible media, such as newspapers, are perceived as more informative than those in less credible media like television. Factors influencing consumer attitudes toward advertising include entertainment, informativeness, irritation, credibility, and demographics.

Interactivity, particularly in online advertising, is also an important factor in shaping consumer perceptions. The literature suggests that a refined understanding of online advertising is necessary to leverage the Internet's strengths as competition for consumer attention grows (Huaiqing Wang, Matthew K.O. Lee, And Chen Wang).

Further, the literature examines the effects of repetition and familiarity on consumer attitudes, drawing from classical theories such as Mere Exposure Theory and the Propinquity Effect. These theories propose that repeated exposure to stimuli can result in more positive attitudes. Mere Exposure Theory, for instance, suggests that familiarity can lead to increased liking, as demonstrated in studies where repeated exposure to stimuli like Chinese characters resulted in stronger positive associations. The Propinquity Effect supports the idea that increased interaction with others fosters positive attitudes. However, the review also acknowledges limitations in these theories when applied to online advertising, suggesting that mere repetition may not be enough to foster positive consumer attitudes. The introduction of personal relevance and interactivity as factors that impact consumer attitudes highlight the need for a more nuanced understanding of how repetitive online advertisements influence consumer perceptions in the digital landscape (Campbell & Wright, 2008).

Lastly, the literature explores consumer perceptions of advertising, specifically focusing on e-CRM and online advertising. Four key factors—entertainment, irritation, informativeness, and credibility—are identified as shaping consumers' perceived value and attitudes toward advertising. Previous research, such as Ducoffe's (1995) work, has shown that these factors play crucial roles in influencing advertising value and consumer attitudes. The inclusion of interactivity as an additional factor in online advertising further enhances consumer engagement and perceptions. The review also discusses the differences between traditional and online advertising, noting that interactivity in the digital realm increases consumer involvement. Additionally, demographic variables such as gender and college major have been shown to influence attitudes toward advertising, though they do not necessarily affect perceived advertising value. Overall, the literature provides a comprehensive understanding of how various factors combine to shape consumer attitudes toward advertising across traditional and digital platforms (Zhang & Wang, 2005).

III. RESEARCH GAP

Personalized display ads have become more and more common in digital marketing, but little is known about how consumers' technological literacy affects how they respond to these ads and whether or not they intend to make a purchase. Previous studies have investigated the efficacy of tailored advertising and diverse elements influencing consumer conduct within digital settings. However little attention has been paid to the particular moderating effect that technology literacy plays. Given the growing complexity of digital platforms and the growing gap in consumer technological proficiency, this gap is especially noteworthy. There isn't a thorough analysis of how different tech literacy levels affect consumers' comprehension, confidence, and interaction with personalized display ads in the body of current knowledge.

In order to close this gap, this study will examine how technology literacy influences the relationship between personalised display ads and customers' intentions to make purchases. The findings will advance the theory of digital marketing research and have real-world implications for advertising strategy customisation.

IV. OBJECTIVE

To determine the factors that influence users' intentions to click on personalized mobile advertisements.

V. METHODOLOGY

The study employs a quantitative research design to investigate the factors influencing the click intension towards mobile app ads, with primary data collected through a structured questionnaire.

The target population consists of consumers exposed to personalized display ads, with a sample size of 200 respondents selected through convenience sampling. The structured questionnaire include sections on demographic information (age, gender, education, income), technology literacy (self-reported levels adapted from existing scales), privacy concerns, trust in AI, Ad design, perceived relevance, and click intention (likelihood of making clicking a personalized ads). The questionnaire was distributed online via social media platforms, email lists, and online forums. Data analysis involved descriptive statistics to summarize demographic characteristics and responses, factor analysis as well as regression to examine the impact of various factors on click intention. The procedure includes designing and the questionnaire, distributing it to the target sample, cleaning the data for accuracy, and performing statistical analyses using SPSS.

VI.   DESCRIPTIVE ANALYSIS

Variable	Categories	Frequency	Percentage
Age	18-24	124	82
	25-35	28	18
Gender	Male	87	57.2
	Female	65	42.7
Qualification	Graduation	76	50
	Post-Graduation	76	50
Annual Income	<20,000	139	91.4
	Between 21,000 - 50,000	4	2.6
	Between 51,000 - 1 Lakh	9	5.9
Employment status	Student	148	97.4
	Employed	2	1.3
	Unemployed	2	1.3
Marital status	Divorced	7	4.6
	Married	6	3.9
	Unmarried	139	91.4

Table - 1

The sample predominantly consists of young adults, with 82% of respondents falling in the 18-24 age range and 97.4% identifying as students. This youthful demographic suggests that the results may be particularly relevant to younger, tech-savvy individuals who are likely to be early adopters of digital trends and personalized advertising. The low annual income of 91.4% of the respondents, combined with the high proportion of students, further underscores the importance of understanding the preferences of this group, especially in the context of personalized digital marketing, which often targets younger, budget-conscious consumers.

Gender representation is relatively balanced, with 57.2% male and 42.7% female respondents, allowing for potential gender-based insights. Additionally, the sample is evenly split between graduates and post-graduates, which could influence findings related to education and its effect on technology literacy and purchase intention. The majority of respondents are unmarried (91.4%), reflecting a group that is still in the early stages of their personal and professional development. This demographic profile points to the significance of personalized display ads that resonate with younger, educated, and tech-literate individuals who may have limited disposable income but are highly engaged with digital content.

Reliability Statistics

Cronbach's Alpha	N of Items
.855	27

Table – 2

The reliability analysis, indicated by a Cronbach's Alpha of 0.855, demonstrates high internal consistency among the items in the scale. A value above 0.7 is generally considered acceptable for reliability, while a value above 0.8 is regarded as good, making 0.855 a strong indicator of consistency. This suggests that the items within the scale are well-correlated and consistently measure the intended construct. The reliability coefficient reassures that the results obtained from these items are dependable and exhibit minimal random error.

The scale, composed of 27 items, has proven to be effective in reliably measuring the target construct. The high Cronbach's Alpha further supports the idea that these items, when taken together, form a cohesive and reliable instrument for data collection. This level of reliability ensures that the findings based on this scale can be considered robust and consistent, strengthening the overall validity of the study's conclusions.

VII. FACTOR ANALYSIS

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.893
Bartlett's Test of Sphericity	Approx. Chi-Square	2789.596
	df	378
	Sig.	.000

Table – 3

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy yielded a value of 0.893, indicating that the sample size is more than adequate for conducting factor analysis. A KMO value above 0.8 is considered good, suggesting that the dataset is well-suited for this type of analysis. This high KMO value signifies that there is sufficient variance in the data to identify meaningful factors, reinforcing the suitability of the sample for the underlying statistical procedures.

Bartlett's Test of Sphericity further confirms the appropriateness of conducting factor analysis. With an approximate Chi-Square value of 2789.596, degrees of freedom of 378, and a significant p-value of 0.000, the test shows that the correlations between items are large enough to allow for the extraction of distinct factors. The significance of this result supports the notion that the items are interrelated and can be grouped into coherent factors, thus validating the overall structure of the data for subsequent analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.002	39.293	39.293	11.002	39.293	39.293	5.177	18.491	18.491
2	2.826	10.094	49.387	2.826	10.094	49.387	4.282	15.294	33.784
3	1.686	6.023	55.410	1.686	6.023	55.410	3.435	12.268	46.052
4	1.593	5.689	61.099	1.593	5.689	61.099	2.812	10.043	56.095
5	1.236	4.416	65.514	1.236	4.416	65.514	2.253	8.046	64.141
6	1.059	3.783	69.298	1.059	3.783	69.298	1.444	5.157	69.298
7	.902	3.222	72.520						
8	.789	2.819	75.338						
9	.719	2.569	77.907						
10	.646	2.306	80.213						
11	.584	2.086	82.299						
12	.545	1.948	84.247						
13	.515	1.840	86.087						
14	.438	1.564	87.651						
15	.405	1.445	89.096						
16	.382	1.365	90.461						
17	.337	1.204	91.665						
18	.326	1.163	92.828						
19	.305	1.091	93.919						
20	.282	1.007	94.925						
21	.275	.982	95.907						
22	.230	.823	96.730						
23	.202	.721	97.450						
24	.190	.680	98.130						
25	.164	.584	98.715						
26	.145	.517	99.232						
27	.120	.430	99.661						
28	.095	.339	100.000						

Table – 3.1

Extraction Method: Principal Component Analysis.

The initial eigenvalues reveal that the first six factors have eigenvalues greater than 1, indicating that they each explain a significant amount of variance in the data. Together, these six factors account for 69.3% of the total variance, which suggests that the majority of the information captured by the dataset is effectively represented by these components. This implies that the dimensionality of the data can be substantially reduced without losing critical insights, as the most important factors are retained.

Following rotation, the variance is more evenly distributed across the six factors, improving the interpretability of the factor structure. The rotation helps to clarify the relationships between variables and allows each factor to explain a more balanced portion of the total variance. This redistribution aids in identifying distinct, meaningful factors, making the results easier to interpret and enhancing the overall clarity of the factor analysis.

Rotated Component Matrix[a]

	Component					
	1	2	3	4	5	6
AD_1	.792					
AD_2	.762					
AD_3	.761					
AD_4	.714					
AD_5	.678					
AD_6	.678					
PC_1		.880				
PC_2		.862				
PC_3		.845				
PC_4		.804				
PC_5		.719				
PR_1			.794			
PR_2			.747			
PR_3			.677			
PR_4			.659			
PR_5			.525			
TL_1				.810		
TL_2				.769		
TL_3				.699		
TL_4				.634		
TAI_1					.810	
TAI_2					.769	
TAI_3					.699	
PV_1						.850
PV_2						.650
PV_3						.762

Table – 3.2

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

The factor loadings from the analysis indicate the strength and direction of the relationship between each variable and its corresponding factor. Variables with high loadings, typically above 0.7, show a strong association with a specific factor. For example, AD1, AD2, and AD3 load heavily on Factor 1, indicating that these variables are strongly related to a common underlying construct, likely related to Ad Design. Similarly, PC1, PC2, and PC3 load heavily on Factor 2, representing a distinct factor that could correspond to Privacy Concerns. PR1, PR2, and PR3 load on Factor 3, suggesting they are grouped together under another construct, potentially Perceived Relevance. This pattern continues for the remaining factors, with each representing a distinct dimension in the data.

The rotated component matrix helps clarify these relationships by grouping related items together into specific factors, enhancing the interpretability of the factor structure. Factor 1 may correspond to Ad Design, Factor 2 to Privacy Concerns, Factor 3 to Perceived Relevance, and so on. This clear grouping of items into distinct factors demonstrates that the variables align well with the theoretical constructs being measured, providing a solid foundation for further analysis.

The factor analysis identifies six distinct factors that collectively explain 69.3% of the total variance in the data. The high KMO value and significant Bartlett's Test of Sphericity confirm that the sample is adequate and the data is suitable for factor analysis. The communalities and rotated component matrix further validate the factor structure, with strong loadings showing clear groupings of related variables. This analysis is instrumental in reducing the dataset to a smaller, more manageable set of factors, which can be leveraged for advanced statistical procedures, such as regression analysis or structural equation modelling, to explore deeper insights.

A. Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.736[a]	.589	.581	.6333

Table - 4

a. Predictors: (Constant), TL, PC, TAI, AD, PR, PV

ANOVA[a]

| Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	68.094	7	9.728	24.258	.000[b]
	Residual	57.745	144	.401		
	Total	125.839	151			

Table – 4.1

a. Dependent Variable: CI

b. Predictors: (Constant), TL, PC, TAI, AD, PR, PV

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	.007	.294		.025	.980		
TL	.569	.079	.514	7.231	.000	.631	1.585
AD	.193	.085	.203	2.265	.003	.395	2.529
PV	-.063	.101	-.059	-.624	.533	.362	2.765
PC	-.031	.065	-.033	-.476	.635	.670	1.492
TAI	.066	.110	.049	.594	.553	.462	2.166
PR	.213	.096	.184	2.217	.001	.462	2.166

Table – 4.2
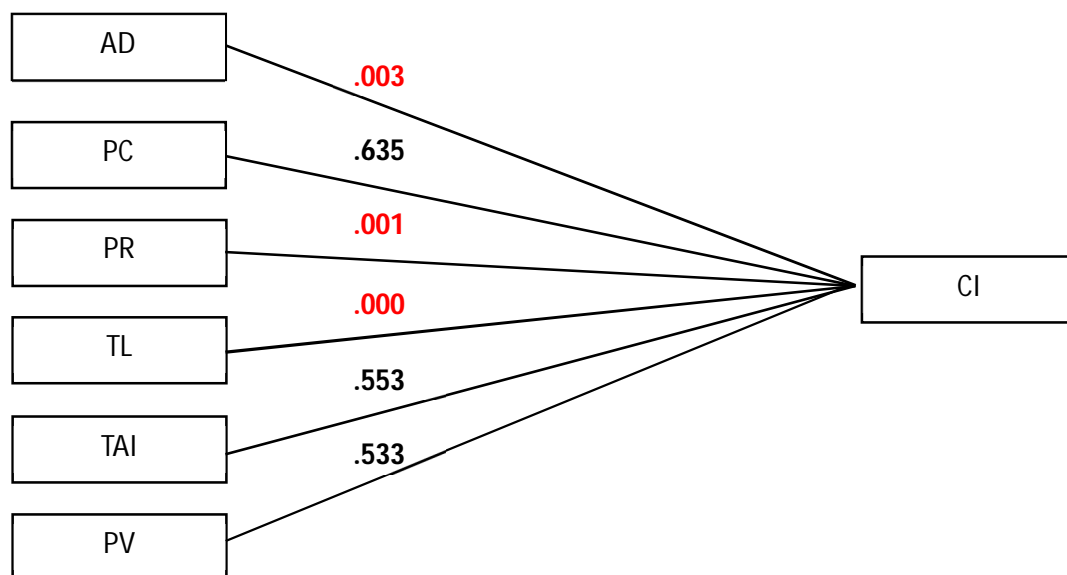
B. Hypotheses

- H1: Technology Literacy (TL) has a significant positive effect on Click Intention (CI).
- H2: Privacy Concerns (PC) have a significant negative effect on Click Intention (CI).
- H3: Trust in AI (TAI) has a significant positive effect on Click Intention (CI).
- H4: Ad Design (AD) has a significant positive effect on Click Intention (CI).
- H5: Perceived Relevance (PR) has a significant positive effect on Click Intention (CI).
- H6: Perceived Value (PV) has a significant positive effect on Click Intention (CI).

The model summary shows a strong correlation between the independent variables (TL, PC, TAI, AD, PR, PV) and the dependent variable, Click Intention (CI), with an R value of 0.736. This suggests a strong relationship between the variables. The R Square value of 0.589 indicates that 58.9% of the variance in CI is explained by the independent variables in the model. The Adjusted R Square, slightly lower at 0.581, accounts for the number of predictors and provides a more accurate measure of the model's explanatory power. Additionally, the standard error of the estimate is 0.6333, indicating the average deviation of the observed values from the regression line. The model is statistically significant, meaning that the independent variables, collectively, significantly predict the dependent variable (Click Intention). The p-value (.000) being less than 0.05 indicates strong evidence against the null hypothesis, suggesting that at least one predictor variable has a significant relationship with Click Intention.

The coefficients of the model highlight the impact of various predictors on Click Intention (CI). Technology Literacy (TL) has a significant positive effect on CI, with a B value of 0.569 (p < 0.001), indicating that for every unit increase in TL, CI increases by 0.569 units. This supports the hypothesis (H1) that TL is a key driver of CI, and its Beta value of 0.514 shows it is the strongest predictor. Similarly, Ad Design (AD) positively influences CI, with a B value of 0.193 (p = 0.003), meaning a unit increase in AD leads to a 0.193-unit rise in CI. The Beta value of 0.203 identifies AD as the second most influential factor, supporting H4. Perceived Relevance (PR) also has a significant positive effect on CI, with a B value of 0.213 (p = 0.001), suggesting a unit increase in PR results in a 0.213-unit increase in CI, and its Beta value of 0.184 shows a moderate influence, supporting H5.

On the other hand, Perceived Value (PV), Privacy Concerns (PC), and Trust in AI (TAI) show no significant impact on CI. PV has a negative coefficient (B = -0.063, p = 0.533), indicating a slight, non-significant decrease in CI, which does not support H6. Similarly, PC shows a small, non-significant negative effect (B = -0.031, p = 0.635), which does not support H2. Lastly, TAI has a positive but non-significant effect on CI, with a B value of 0.066 (p = 0.553), and H3 is also not supported.

C. Summary of Hypotheses Testing

- Supported: H1 (TL), H4 (AD), H5 (PR)
- Not Supported: H2 (PC), H3 (TAI), H6 (PV)

Overall, the results suggest that Technology Literacy, Ad Design, and Perceived Relevance are significant predictors of Click Intention, with Technology Literacy having the most substantial impact. Privacy Concerns, Trust in AI, and Perceived Value do not significantly influence Click Intention in this model.

VIII. CONCLUSION

The study highlights the significant influence of Technology Literacy (TL), Ad Design (AD), and Perceived Relevance (PR) on consumers' Click Intentions (CI). Among these, Technology Literacy plays the most critical role, suggesting that individuals with higher technological proficiency are more likely to engage with personalized digital advertisements. This finding highlights the growing digital divide in society, where those with advanced tech skills can better navigate and benefit from personalized marketing campaigns. As a result, marketers must develop strategies that account for varying levels of tech proficiency to ensure inclusivity, particularly for those who may not be as tech-savvy.

For policymakers, the study emphasizes the need to promote digital literacy to ensure equitable access to digital marketing platforms and tools. By enhancing digital education and accessibility, policymakers can help bridge the gap between tech-savvy and less technologically proficient consumers, ensuring that all individuals can engage with and benefit from personalized advertising. Moreover, the findings suggest the need to revisit consumer protection policies, especially concerning privacy concerns and the role of AI in marketing. Although these factors did not significantly impact consumer behavior in this study, they remain crucial areas for further exploration, particularly in the context of growing digital marketing practices.

When compared with existing literature, this study aligns with prior research highlighting the importance of personalized content, ad design, and relevance in influencing consumer attitudes and behaviors. However, it adds a unique contribution by exploring the moderating role of technology literacy, an aspect that has been underexplored in previous studies. The research addresses the identified gap in the literature regarding how consumers' technological competencies affect their engagement with personalized ads. Despite this, further research is required to examine the role of privacy concerns and trust in AI, which did not emerge as significant predictors in this study, but may vary across different consumer segments or future digital landscapes.

In conclusion, the study finds that Technology Literacy is the strongest predictor of Click Intentions, followed by Ad Design and Perceived Relevance. These findings offer valuable insights for digital marketers, emphasizing the need to tailor advertising strategies based on consumers' technological capabilities. While factors such as privacy concerns, trust in AI, and perceived value did not significantly influence click intentions, they remain critical for future research and digital marketing considerations as technology and consumer awareness evolve. The results have implications for both marketing strategies and policy development, with a focus on fostering digital inclusivity and protecting consumer rights in an increasingly digital marketplace.

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