

Extending TPB with Culture and Habit: The Moderating Role of Search Engine Usage Frequency in User engagement of Search Engine marketing

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Abstract: The psychological and social motivation of engagement with Search Engine Marketing (SEMR) is important in the development of effective user-focused digital strategy. Although the role of SEMR is becoming more dominant in the field of online advertising, most of the previous studies on the topic were advertiser-centric, with little focus on the perception and views of the user. The paper fills this gap by referring to the Theory of Planned Behavior (TPB) to analyze how attitude towards SEMR (ATU), subjective norm (SN), and perceived behavioral control (PBC) influence behavioral intention (BI). According to a survey of 258 participants, which were modelled using structural equation, findings indicate that SN and PBC have a significant impact on ATU, and all three predictors have a positive effect on BI. ATU facilitates the impacts of SN and PBC on BI. Building on TPB and extending it with the cultural dimensions of Hofstede, the researcher finds no meaningful moderating variable of frequency of search engine use, with culture and perception being the more significant factors that dictate the presence of SEMR engagement.

Keywords: Search Engine marketing, perception on part of the population, behavioral

1. Introduction

Search Engine Marketing has become one of the strongest tools of the development of virtual world products and services perception, comparison, and choice process of people. It enables organizations to contact customers at key information search stages, which affects their desire to read business content [1]. Although the world is actively investing in SEMR, the majority of the existing studies are centered on advertisers, their attention on designing the algorithm, efficiency of bids, performance of campaigns, and similar factors [2]. This tendency has left a theoretical gap in user experience, particularly the impact of psychological and social elements on paid search results perceptions, assessments, and reactions [3]. Since the end result of SEMR is the user's willingness to use sponsored results, these behavioral processes must be understood. The Theory of Planned Behavior defines intention to carry out the behavior as attitude to the behavior, perceived social expectations, and perceived control over the behaviour [4]. Pro-environmental behavior, mobile payment acceptance, and social commerce involvement have all been successfully implemented using this theoretical paradigm [5,6]. However, experts have noted that the Theory of Planned Behavior needs more development to match digital environments because acts are rapid, repetitive, and culturally prescribed and habitual [7]. Users interact in SEMR in a common, spontaneous manner, driven by cognitive shortcuts rather than conscious thought.

Habitual behavior and search frequency are important. Repeated activities become automatic and less intentional.



Norman [8] states that as a conduct becomes habitual, intentions become less predictive. When habits are strong, Gardner, de Bruijn, and Lally [9] found that intention predicted behavior becomes less influential. This suggests that search engine heavy users may react to adverts out of habit rather than intention. This moderating effect of search frequency as a habit has not been investigated in digital advertising.'

Cultural considerations can affect how people react to online information. Hofstede and Minkov [10] highlighted individualism, collectivism, and uncertainty avoidance as cultural factors that explain why people behave and desire differently in different civilizations. Yoon [11] and Bianchi and Andrews [12] found that cultural values affect online trust, perceived risk, and purchasing behavior. Collectivist cultures rely more on social expectations when making behavioral intentions in digital marketing, while individualistic cultures focus more on personal opinions. Although these points have been discovered, SEMR cultural disparities are not fully studied, even though users in different cultures may view search results differently.

This study work builds a protracted theory of planned behavior model to understand SEMR user behavior based on these findings. It studies how SEMR attitude, perceived social expectations, and perceived control affect behavioral intention. It also examines whether search engine use frequency mediates attitude-behavioral intention links and how cultural values do. Perceived social expectations, perceived control, and behavioral intention all affect attitude in a cross-sectional survey of 258 respondents, supported by structural equation modeling. Regular search engine use does not affect the relationship between attitude and behavioural intention, hence habitual use is not the main determinant in search ad responsiveness.

The current research would benefit the field in three ways. First, it adds culture and habitual search behavior as boundary conditions to make behavioral theory more applicable to digital marketing research. Second, applying this theoretical model to SEMR through the user's lens provides empirical evidence in a subject that has not been extensively investigated. Third, it offers advice to marketers who want to create culturally responsive, socially relevant, and user-friendly search advertising campaigns that appeal to trust and perceived control rather than habitual interaction.

2. Review of Literature and Hypothesis Development

2.1 Attitude Towards Use and Behavioral Intention.

Recent studies by SEMR have emphasized user perception and use as the driver of SEMR success not only depending on algorithmic features [13],[14]. As SEMR provides immediate visibility as opposed to SEO [15] positive attitudes towards the relevance and value of ads are important determinants of intention.

H1: Attitude Toward Use has a positive correlation with Behavioral Intention.

2.2 Attitude to and Subjective Norms of Use.

The cross-channel interactions can affect the decisions of users [16], i.e. social signals of peers or influencers can impact the perception of acceptability of SEMR engagement. Subjective norms have stronger support of positive attitudes toward SEMR ads as consumers become more and more accepting of algorithmic systems [17].

H2: The positive influence of Subjective Norms on Attitude Towards Use exists.

2.3 Perceived Behavioral Control and Attitudes to Use.

In spite of the fact that SEMR uses algorithmic bidding and targeting [18], manipulative designs can easily damage trust [19]. Attitude is enhanced when users feel that they are in complete control of their ad experience.

H3: There exists a positive relationship between Attitude Towards Use and Behavioral Perceived Control.

2.4 Perceived Behavioral Control and Behavior intention.

Since SEMR is an in-search environment, users who consider themselves competent to control ads demonstrate more intention to interact. This is in line with TPB where intention is directly proportional to perceived control.

H4: Perceived Behavioral control is positively correlated with the Behavioral Intention.

2.5 Behavioral Intention and Subjective Norms.

Social recommendation and cross-channel influence influence the behavior[16], boosting intention when social reinforcement of SEMR engagement structure is present.

H5: The positive Behavioral Intention is influenced by the Subjective Norms.

2.6 Extension of TPB: Cultural and Habitual - Frequency of Search Engine Use.

The habitual familiarity of frequent search reduces the effort and makes the attitude-intention relationship stronger [20]. Such cultural dispositions as uncertainty avoidance endorse the existence of digital routine [10].

H6: The relationship between ATU and BI is moderated by the frequency of search engine use in the sense that, the more the frequency, the stronger the relationship.

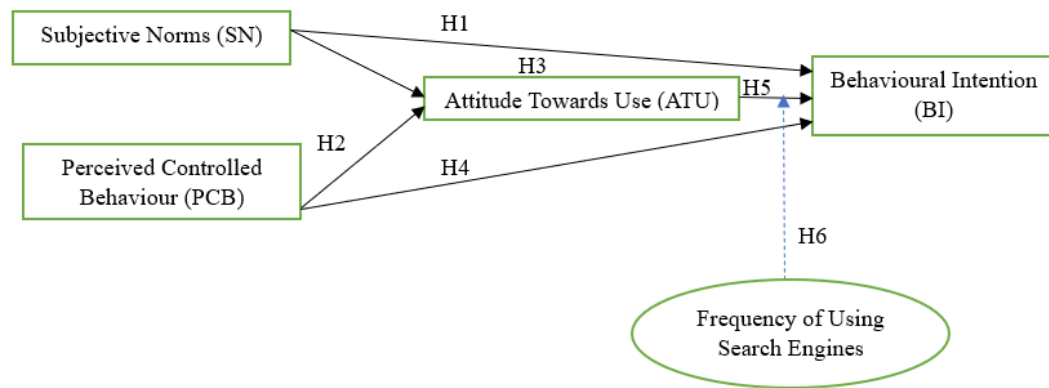


Fig.1 Author's model for the study

3. Methodology

3.1. Respondents and Techniques

The behavior and opinions of SEMR users were examined using a cross-sectional survey, a typical method for studying technology adoption [21]. An online structured questionnaire ensured a large number of replies and a diverse sample depicted in table 1.

Source: Authors work

Table 1: Sample Demographics (n=258)

Sl.no	Aspects	Categories	Prevalence	Percentage
1	Age	18-24	61	23.6
		25-34	152	59.0
		35-44	21	8.1
		45-54	11	4.3
		55-64	13	5.0
2	Gender	Male	147	57.1
		Female	109	42.2
		Transgender	2	.6
3	Marital Status	Married	117	45.3
		Divorced	3	1.2
		Separated	5	1.9
		Unmarried	131	50.9
		I prefer not to say	2	.6
4	Educational Qualification	High School	6	2.5
		Diploma	22	8.7
		Graduate	114	44.1
		PG and above	115	44.7
5	Occupation	Student	42	16.1
		Employee	168	65.2
		Self-employed	18	6.8
		Retired	5	1.9
		Unemployed	19	7.5
		Others	6	2.5
6	Geographical Location	Urban	162	62.7
		Rural	50	19.3
		Suburban	43	16.8
		Other	3	1.2
7	Frequency of using Search engines	Daily	213	82.6
		Weekly	29	11.2
		Rarely	16	6.2
8	Search engines being used primarily	Google	250	96.9
		Bing	3	1.2
		Duck Duck Go	3	1.2
		Others	2	.6

To generate unbiased user outcomes, digital marketing research uses basic random sampling [42]. After eliminating incomplete or inconsistent replies from 292 initial respondents, 258 active search engine users were left. Public users are SEMR tactics' core audience, hence they must be analyzed[22].

The questionnaires targeted SEMR ad users on social media, email lists, and online forums. Subjective Norms (SN), Perceived Behavioral Control (PBC), Attitude Toward Use (ATU), and Behavioral Intention (BI) were measured using established TPB measures with structured questions. The study purpose was described, informed consent was acquired, and respondents participated anonymously in compliance with ethical norms [22].

Most (59 and 23.6%, respectively) were 25-34 and 18-24 years old; 57.1 percent were male, 42.2 percent female, and 0.6 percent transsexual. Of the 44,1% graduates and 44.7% postgraduates, 62.7% lived in cities and 65.2% worked. The majority (82.6) searched daily, and 96.9% of workers liked Google, reflecting global market dominance.

3.2. Measures

This questionnaire measure was developed using the known scales of measurement of previous studies to measure variables associated with the adoption of SEMR. All the answers were scored with five points Likert scale, one being a strongly disagree and five a strongly agree.

Subjective Norms (SN): Measured on a scale of perceived social influence by others (peers), experts, and organizations, and is determined on the Theory of Planned Behavior[4].

Perceived Controlled Behaviour (PCB): This measure was measured in relation to the perceived control of users over their interaction with SEMR in regard to ease of access and the confidence of using SEM ads [4].

Attitude Toward Use (ATU): It is measured by an item based on the Theory of Planned Behavior so as to provide a high level of reliability [4].

Behavioral Intention (BI): This is measured on a validated scale, which is very reliable [23].

Table 2: Reliability analysis

Construct	Cronbach's Alpha	CR	AVE
Attitude towards Use	0.934	0.917	0.735
Behavioural Intention	0.928	0.939	0.837
Perceived Controlled Behaviour	0.916	0.880	0.649
Subjective Norms	0.939	0.918	0.736
Overall Reliability	0.878		

Source: Author's Work

3.3. Analysis Method

The adoption factors of SEMR were analyzed through a rigorous method which was statistically based. The sample profile was summarized using descriptive statistics as internal reliability was assessed based on Cronbach alpha value >0.70 and acceptable item-total correlations. A KMO score of 0.854 and outstanding results of Bartlett test ($p < .001$) supported the sampling adequacy. PCA and Varimax rotation and factor loadings greater than 0.50 assured construct validity which was further verified using AMOS CFA and model-fit indices. The hypothesized relationships were tested and complex interdependencies were considered using SEM. The indirect effects were measured through bootstrapping ($n=5,000$) and moderation checked by means of hierarchical regression and multi-group SEM. The rigor of the methodology gives it a strong basis in determining user-centric determinants of SEMR adoption.

4. Results

In this section, the research findings involving the impact of user-centric factors on BI towards SEMR are provided.

4.1 EFA results

The value of KMO = 0.896 justifies the use of the factor assessment and confirms the sufficiency of the sample using the Test of Sphericity that demonstrates that the correlations among variables are strong ($kh2 = 847.334$, $df = 10$, $p = 0.001$) [24],[25].

A large factor - user-centric factor was found, which explained 84.19 percentage of the total variance (Eigenvalue = 4.210) which is more than Kaiser criterion of 1.0 [26]. The existence of high commonalities (0.745-

0.883) and strong factor loadings (0.863-0.939) of all the variables indicates a strong unidimensional structure. There was no need to do rotation, and only one component was obtained.

CFA analysis of such a structure identified a coherent construct in favor of behavioral intention, which is in line with TPB theory.

4.2 CFA results

Based on the CFA output, the measurement model has good model fit, reliability and validity. The values of Composite Reliability (CR) assures internal consistency of all constructs with a range of 0.880 to 0.939 (Table 2) and even exceeding the recommended 0.70 level [27]. The values of the Average Variance Extracted (AVE) confirm the values of convergent validity and the variance ranges between 0.649 and 0.837, which is above the 0.50 range [21].

The Fornell-Larcker Criterion was used to determine discriminant validity (Table 3) and as can be seen, the AVE square root of each construct outweighed its correlation to other constructs. This provides theoretical validity as it proves independence of constructs [27].

Table 3: Discriminant validity

	SN	PCB	ATU	BI
SN	0.858	-	-	-
PCB	0.000	0.806	-	-
ATU	0.000	0.000	0.857	-
BI	0.000	0.000	0.000	0.915

Source: Author's Work

The outcome of the measurement model brought about a good fit with RMSEA = 0.046, CMIN/DF = 1.338 and RMR = 0.035. It is also strong evidenced by the high CFI (0.984), IFI (0.984), and TLI (0.981) [28],[29],[30].

These results support the measurement framework in the TPB model, thus guaranteeing construct reliability and validity. The good fit of the model is an affirmation of the fact that the latent constructs successfully measure construct-relationships. The verified structure can be further used in testing hypotheses and structural models to provide a strong base on which technology adoption behaviors can be analyzed.

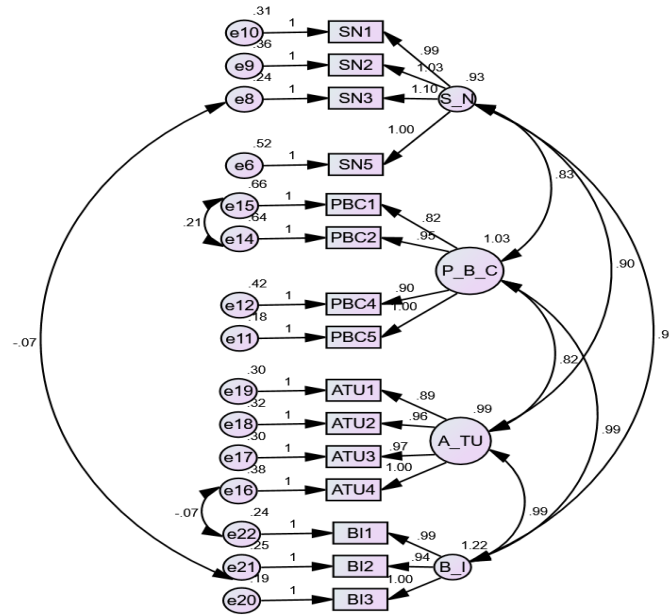


Fig 2: Confirmatory Factor analysis

4.3 Common Method Bias (CMB)

There were several ways to control Common Method Bias (CMB) and Social Desirability Bias (SDB). First, Variance Inflation Factor (VIF) values were checked, and all were below the crucial value, indicating that multicollinearity is not a problem [31]. Podsakoff et al. [32] found that Harman's one-factor test explained less than 50% of CMB's absence. Anonymity and questionnaire constraint were also implemented in the study. The SEM model fit declined after adding a latent method factor (CMIN/DF = 2.108, RMSEA = 0.083), while the baseline model without the method factor fit better (CMIN/DF = 0.855, RMSEA = 0.000). This suggests that CMB is unaffected and that the initial model better represents the data. Longitudinal data or marker variables may also correct technique bias in future studies.

4.4 SEM results

The model fit statistics show that the suggested structural model models the data perfectly, as shown in Figure 3. The Chi-square score (CMIN/DF = 0.855, $p = 0.355$) is below 3.0, indicating that the model fits well [32]. RMSEA is 0.000, far below the 0.08 limit for a satisfactory model fit [28]. Other fit indices, such as Comparative Fit Index (1.000), Normed Fit Index (0.999), and Incremental Fit Index (1.000), are over 0.90, confirming that the model matches the data [29]. The Standardised root mean square residual (RMR = 0.004) and Goodness-of-Fit Index (GFI = 0.998) also support a good model [32].

A large incremental fit indices (CFI, IFI, NFI) indicate that the theoretical model is very suitable in understanding user behavior, which confirms the TPB. RMSEA and RMR are small, which implies that there is a moderate model misspecification and high correlations between SN, PCB, and BI. The high GPI of the model suggests that the model is in line with the data, which is useful in the digital marketing and e-commerce environment. These results indicate

that the ease of design, social impact, and perceived control are the elements that organizations should emphasize to enhance the use of technology. Findings can be applied by the marketers and politicians to get additional user engagement and behavior.

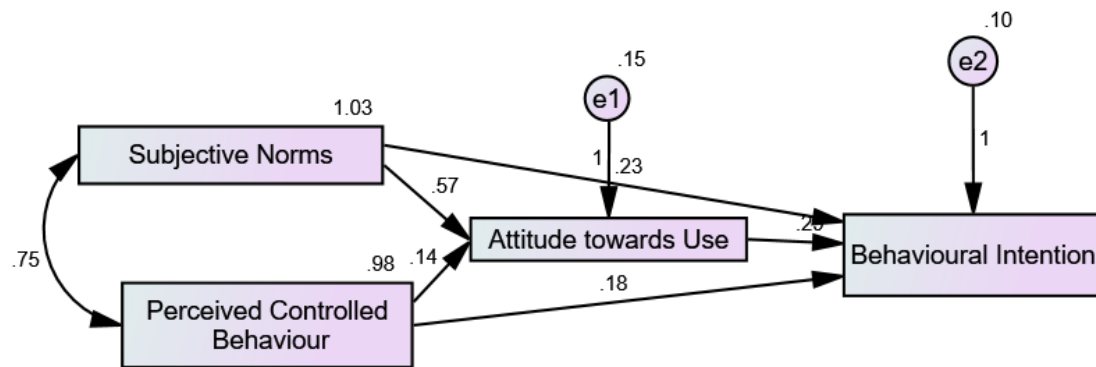


Fig 3: Structural Equation Modelling results of the model

4.5 Moderation Analysis

Moderation hypothesis (H6) proposed that search engine use frequency moderates the association between ATU and BI. The structure was fitted using the computed interaction term (ATU x Frequency). It did not moderate since the interaction term was non-significant ($b = 0.006$, S.E. = 0.013, $p = 0.670$). This model's squared multiple correlation of $R^2 = 0.061$ showed that the interaction explained just 6% of BI's variance. The model fit well despite the non-significant moderation ($\chi^2 = 0.568$, $DF = 1$, $p = 0.451$; CFI = 1.000; RMSEA = 0.000, PCLOSE = 0.534).

The findings contradict Hofstede Cultural Dimensions Theory, which indicated that frequent search engine users would respond based on their own views in high individualism and low uncertainty-avoidance countries, boosting the ATU-BI association. Habitual search increases familiarity, less ambiguity, and confidence, which leads to more positive attitudes and behavioral intentions. The lack of a substantial moderating effect suggests that in the cultural setting of this study, ATU's impact on BI is unaffected by search frequency. The respondents' collectivism may explain why they base their decisions on societal standards rather than personal preferences. Even frequent searchers may demand communal validation against individual judgment due to moderate-high uncertainty avoidance. Cultural tendencies may offset the frequency of use, making moderation insignificant.

Table 4: Hypothesis Testing Results

Hypothesis	Path	Estimate (β)	SE	95% CI (LCL–UCL)	Result
H1	SN → ATU	0.573	0.045	0.485 – 0.661	Supported
H2	PCB → ATU	0.140	0.046	0.050 – 0.230	Supported
H3	SN → BI	0.232	0.052	0.130 – 0.334	Supported
H4	PCB → BI	0.179	0.038	0.105 – 0.254	Supported
H5	ATU → BI	0.286	0.064	0.161 – 0.411	Supported
H6	Frequency of Using Search Engines × ATU	0.006	0.013	–0.019 – 0.031	Not Supported

	→ (Moderation)	BI				
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Source: Author's Work

As per the results, H1 ($\beta = 0.573$, $p < 0.001$) is accepted, which proves that the Subjective Norms have a positive effect on the Attitude towards Use (ATU). This implies that the more the users feel that there is great social approval/peer pro-SEMR, the more they are prone to developing positive attitudes towards it. This finding is consistent with the Theory of Planned Behavior[4] that focuses on social influence to form attitudes. The previous research also indicates that peer and society acceptance has a strong impact on the involvement of online advertising [35],[36].

H2 ($\beta = 0.140$, $p = 0.002$) is supported as well, which means that Perceived Behavioral Control affects ATU positively. The more empowered the user is to have control over his or her ad interaction like the ability to skip, filter or to click, the more the user will develop positive attitudes towards SEMR. This outcome is in line with the previous studies found that perceived control leads to increased user confidence and decreased resistance to advertisements [37],[38].

The findings also support H3 ($\beta = 0.232$, $p > 0$), which shows that SN has a positive effect on Behavioral Intention. Users become willing to interact when they think that SEMR engagement is socially appreciated by others or online groups. This confirms TPB assumptions [4], and it fits the evidence of digital advertising, which emphasizes the convincing influence of social evidence and peer approval [39],[37].

On the same note, H4 ($\beta = 0.179$, $p < 0.001$) is significant, indicating that PBC has a direct impact on BI. Users who believe that they can manage SEMR interactions will be more likely to do so voluntarily in line with earlier results that perceptions of control lead to participation and decrease ad avoidance [41],[36].

H5 ($\beta = 0.286$, $p < 0.001$) is also confirmed and indicates that ATU has a positive influence on BI. Positive attitudes to SEMR enhance the chances of real involvement as the mediation of attitudes in TPB is important [4]. This is aligned with digital marketing findings that indicate positive attitudes towards ads to increase both click-through and engagement rates [39],[40].

Lastly, H6 ($\beta = 0.006$, $p = 0.670$) is not significant which shows that Frequency of Search Engine Use does not moderate the ATU-BI relationship. Therefore, there is no strengthening or weakening of the effect of the attitudes on behavioral intentions by habitual search use. Even though the frequent user experiences contact with search engines on a daily basis, it does not mean that responsiveness to SEMR is enhanced. In contrast to the cultural expectation of Hofstede, high collectivism or uncertainty avoidance failed to increase the habitual effects. These results indicate that cultural and perception factors, and not the usage frequency, have a stronger influence on determining SEMR engagement.

5. Implications

5.1 Theoretical Contributions

The given work is the continuation of the Theory of Planned Behavior (TPB) that considers Frequency of Search Engine Use as the possible moderator of the Attitude-Behavioral Intention relationship, but it is presented in the context of the Hofstede Cultural Dimensions. Though moderation was not corroborated, findings point out to the contribution of cultural context to technology adoption. In particular, the habitual use of technology has a small contribution towards transforming attitudes into intentions in cultures with high uncertainty avoidance and collectivism. Rather, subjective norms and perceived behavioral control are more predictive behavioral variables.

These results confirm the extensions of TPB that propose the attitudes are formed by experiential variables such as frequency of usage and not moderate behavior. The addition of Hofstede dimensions adds further to the importance of culture-sensitive models of behavior and the necessity to cross-culturally verify before considering the effect of digital adoption being universal.

The present study is in favor of broadening behavioral frameworks with automation, data ethics, and user transparency-highlighting that SEMR interaction needs to be connected with the general issues of user autonomy, ethical design, and mediation by technology [16],[17].

5.2 Implications on Digital Marketers and SEMR Practitioners.

In the case of SEMR professionals, the results emphasize the core TPB predictors being more important than habitual usage in influencing adoption. In as much as usability is essential, ease of use is not enough since positive user attitudes entail explicit ad interfaces, clear disclosures and user-friendly landing pages. Considering the power of subjective norms, the habit of influencer endorsement, peer content, and social proof is suitable to increase engagement. Trust and transparency are ensured by ethical advertising, accurate information, and following GDPR and CCPA strictly. When it comes to AI-driven personalization, message relevancy can be enhanced, although marketers should make sure that they do not bias their algorithm or misuse their capabilities to create prejudice targeted at a specific audience or cause distrust among users.

5.3 Business implications of the strategy to the business leaders.

The business leaders in the wider reach should take on cross-platform marketing that involves the use of search tools, social tools, video tools, and influencer tools. The critical element is that of cultural alignment; the campaigns must be founded on the principles of the target markets as social influence is more significant than habitual use in collectivist or high uncertainty culture. Leaders should enhance brand safety by relying on the consent-based privacy systems and by taking proactive steps against fake content. Finally, flexibility, continued surveillance, and data-driven real-time optimization can make the SEMR strategies more responsive to the variability in consumer and platform relationships.

6. Conclusion

This paper raises out that the user centric influences are the ones that have the most impact on the SEMR acceptance. Its success depends on the personalized, ethical, and AI-based marketing derived on the usability, social influence, and trust. The mixture of data-oriented insights, social policies, and ethical principles enable the companies to make the interaction and the formation of sustainable online development.

7. Limitations and Future Horizons

The nature of the cross-sectional design in this study makes the study incapable of causing the relationships, and also long-term studies will be necessary to track the relationship. The self-reported data may be biased, and that is why observational research or experimental research should be used which means that the sample demographics will be limited to allow generalizations, future research should use various groups of people to reflect the differences in cultures. Moreover, the research on the AIs marketing ethics and privacy aspects should be studied more thoroughly. It is perhaps wise to combine qualitative and computational studies and give more detailed results to learn more about SEMR and user interaction processes.

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Informed consent: Informed consent was obtained from all participants prior to their inclusion in the study in accordance with ethical guidelines.

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REFERENCES

1. Järvinen J, Karjaluo H. The use of Web analytics for digital marketing performance measurement. *Ind Mark Manag.* 2015;50:117–127.
2. Sahni NS, Nair HS. Advertising as a signal. *Mark Sci.* 2019;38(1):77–99. doi:10.1287/mksc.2018.1132
3. Schultheiss S, Lewandowski D. Understanding paid search advertising. *J Assoc Inf Sci Technol.* 2021;72(2):230–243. doi:10.1002/asi.24410
4. Ajzen I. The theory of planned behavior. *Organ Behav Hum Decis Process.* 1991;50(2):179–211. doi:10.1016/0749-5978(91)90020-T
5. Han H, Kim Y. Eco-friendly attitudes and behavioral control. *Sustainability.* 2019;11(8):2218. doi:10.3390/su11082218
6. Sharma SK, Sharma H. Trust and mobile banking usage. *Int J Inf Manag.* 2019;44:65–75. doi:10.1016/j.ijinfomgt.2018.09.013
7. Conner M, Norman P. *Predicting and changing health behaviour: Research and practice of the theory of planned behaviour.* 3rd ed. Maidenhead: Open University Press; 2015.
8. Norman P. (2006) *The role of habit and intention in health behavior change.* Br J Health Psychol. 11(4):505–518.
9. Gardner B., de Bruijn G.J., Lally P. (2012) *Habit, identity, and repetitive action: A prospective study of behavioral automaticity.* Eur J Soc Psychol. 42(3):338–348.
10. Hofstede G, Hofstede GJ, Minkov M. *Cultures and organizations: Software of the mind.* 3rd ed. New York: McGraw-Hill; 2010.
11. Yoon C. National culture and e-commerce acceptance. *Inf Manag.* 2009;46(5):294–301. doi:10.1016/j.im.2009.06.001
12. Bianchi C, Andrews L. Risk and trust in online purchasing. *Int Mark Rev.* 2012;29(3):253–275. doi:10.1108/02651331211229750
13. Boerman SC, Kruikemeier S, Zuiderveen Borgesius FJ. Online behavioral advertising: A literature review and research agenda. *J Advert.* 2017;46(3):363–376. doi:10.1080/00913367.2017.1339368
14. Ahn J, York S. Perceived credibility in digital advertising: Examining search engine marketing effectiveness. *J Interact Advert.* 2021;21(4):312–329.
15. Ghose A, Yang S. An empirical analysis of search engine advertising. *Manag Sci.* 2009;55(10):1605–1622. doi:10.1287/mnsc.1090.1054
16. Filippou G, Georgiadis AG, Jha A. Web traffic and purchase behavior. *Mark Lett.* 2023;35(1):59–71. doi:10.1007/s11002-023-09700-8
17. Raveendhran R, Fast NJ. Human-free behavior tracking products. *Mark Lett.* 2024;35(3):395–408. doi:10.1007/s11002-024-09726-6.
18. Edelman B, Ostrovsky M, Schwarz M. Internet advertising and the generalized second-price auction. *Am Econ Rev.* 2007;97(1):242–259. doi:10.1257/aer.97.1.242
19. Runge J, Wentzel D, Huh JY, Chaney A. Dark patterns in online services. *Mark Lett.* 2022;34(2):155–160. doi:10.1007/s11002-022-09629-4
20. Oulasvirta A, Rattenbury T, Ma L, Raita E. Habits and smartphone use. *Pers Ubiquitous Comput.* 2012;16(1):105–114. doi:10.1007/s00779-011-0411-2
21. Hair JF Jr, Black WC, Babin BJ, Anderson RE. *Multivariate data analysis.* 7th ed. Upper Saddle River (NJ): Prentice Hall; 2010.
22. Jansen BJ, Resnick M. Searchers' perceptions of sponsored and non-sponsored links. *J Am Soc Inf Sci Technol.* 2006;57(14):1949–1961. doi:10.1002/asi.20423
23. Venkatesh V, Morris MG, Davis GB, Davis FD. *User acceptance of information technology: Toward a unified view.* MIS Q. 2003;27(3):425–478.
24. Bartlett MS. *A note on the multiplying factors for various chi square approximations.* J R Stat Soc Series B Stat Methodol. 1954;16(2):296–298.
25. Kaiser HF. *The application of electronic computers to factor analysis.* Educ Psychol Meas. 1960;20(1):141–151.
26. Kaiser HF. *An index of factorial simplicity.* Psychometrika. 1974;39(1):31–36.
27. Fornell C, Larcker DF. *Evaluating structural equation models with unobservable variables and measurement error.* J Mark Res. 1981;18(1):39–50.
28. Hu LT, Bentler PM. *Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives.* Struct Equ Modeling. 1999;6(1):1–55.
29. Bentler PM. *Comparative fit indexes in structural models.* Psychol Bull. 1990;107(2):238–246.
30. Hooper D, Coughlan J, Mullen MR. *Structural equation modelling: Guidelines for determining model fit.* Electron J Bus Res Methods. 2008;6(1):53–60.

31. Hair JF Jr, Hult GTM, Ringle CM, Sarstedt M. *A primer on partial least squares structural equation modeling (PLS-SEM)*. 2nd ed. Thousand Oaks (CA): Sage; 2017.
32. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. *Common method biases in behavioral research: A critical review of the literature and recommended remedies*. *J Appl Psychol*. 2003;88(5):879–903.
33. Byrne BM. *Structural equation modeling with AMOS: Basic concepts, applications, and programming*. New York: Routledge; 2016. doi:10.4324/9781315757421.
34. Renganathan R, Balasubramanian R, Sathish S. *Customer satisfaction in e-banking services: An empirical analysis*. *Int J e-Serv Sci Technol*. 2012;5(1):15–27.
35. Ting H, Ming WT, de Run EC, Choo SY, Cheah JH. *Online engagement and social media usage: Predictors of consumer intention and behavior*. *Int J Bank Mark*. 2019;37(3):126–145.
36. Wang Y, Hong A, Li X, Gao J. *Marketing innovations during a global crisis: A study of digital transformation and consumer engagement*. *J Bus Res*. 2021;136:187–195.
37. Pavlou PA, Fygenonson M. Understanding and predicting electronic commerce adoption. *MIS Q*. 2006;30(1):115–143. doi:10.2307/25148720.
38. Rodgers S, Thorson E. Digital advertising and consumer perception. *J Interact Mark*. 2017;40:1–14. doi:10.1016/j.intmar.2017.06.004
39. Kim J, Park E. *The role of social influence and innovation characteristics in mobile commerce adoption*. *Technol Soc*. 2019;59:101262.
40. Yadav MS, Pavlou PA. *Technology-enabled interactions in digital commerce: A conceptual foundation*. *J Acad Mark Sci*. 2020;48(1):132–151.
41. Pavlou PA, Stewart DW. *Interactive advertising: A new conceptual framework toward identifying its impact on the marketplace*. *J Advert*. 2015;44(1):5–25.
42. Saunders M, Lewis P, Thornhill A. *Research methods for business students*. 8th ed. Harlow (UK): Pearson Education; 2019.