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Research Article

Psychological Determinants of Consumer Acceptance of AI Marketing Technologies: A TRAM Analysis Using SmartPLS

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Abstract: In this study, we use a hybrid model that combines the Parasuraman Technology Readiness (TR) index and the Davis Technology Acceptance Model (TAM) to examine the psychological factors that influence consumers' willingness to adopt AI marketing technologies. Chatbots driven by artificial intelligence, customized recommendation engines, predictive analytics ads, and AI-enabled voice assistants were the four settings used to recruit 487 customers for a cross-sectional quantitative survey. Parametric Least Squares Structural Equation Modeling (PLS-SEM) implemented in SmartPLS 4.0 was used for data analysis. Composite reliability (CR), heterotrait-monotrait ratios (HTMT), average variance extracted (AVE), and discriminant validity were all shown in the assessment of the measurement model. Perceived usefulness ($b = 0.312$, $p <.01$) and perceived ease of use ($b = 0.287$, $p <.01$) were both positively impacted by technological readiness, according to the structures model. Attitude toward AI was impacted by both perceived usefulness and perceived ease of use, which in turn were predicted by perceived usefulness ($b = 0.401$, $p <.001$) and perceived ease of use (PU: $b = 0.356$; PEOU: $b = 0.298$). Attitude was the primary factor in determining actual use behavior, and it was the strongest predictor of behavioral intention ($b = 0.443$, $p <.001$). A total indirect impact of 0.335 (95% CI [0.261, 0.413]) was shown by the mediation analysis, which demonstrated that TAM constructs entirely mediated the link between TR-behavioral intention. Generation Z had the greatest route coefficients throughout the model, indicating a substantial generational difference, according to multi-group analysis. In addition to providing useful implications for the strategy for adopting new technologies, these findings advance TRAM theory within the context of AI marketing.

Keywords: Technology Readiness and Acceptance Model, TRAM, AI marketing, SmartPLS, PLS-SEM consumer acceptance, perceived usefulness, behavioral intention, multi-group analysis

INTRODUCTION

The proliferation of AI technology in marketing ecosystems has caused a sea change in the dynamics between brands and consumers. No longer a peripheral technology, AI-based marketing tools come in both the form of conversational chatbots managing real-time customer enquiries and algorithmic recommendation engines, which create customized shopping journeys. Although their adoption may be fast, there remains a gap between introducing AI marketing technologies and them being embraced wholeheartedly by consumers. Both academics and businesses with an eye toward strategic advantage must consider the feasibility of psychological variables impacting or impeding adoption if they are to reap the benefits of new technologies.

The most well-known of these older models is Davis's Technology Acceptance Model (TAM), which states that consumers' impressions of a product's utility and its perceived ease of use are the most important factors in determining whether or not they will choose to adopt it. Taking this a step further, Parasuraman's Technology Readiness (TR) construct acknowledges that consumers bring optimism, inventiveness, discomfort, and insecurity into technology encounters, which influence how they process technology-related stimuli. The fact that TR and TAM are integrated into the Technology Readiness and Acceptance Model (TRAM) thus provides a more theoretically rich prism to consider the dynamics of adoption which makes it capture both the motivational energy, which drives acceptance, and the cognitive apprehensions which hinder acceptance.

Precedent TRAM studies have been implemented to situations such as mobile banking, e-government services, healthcare information systems and education technology. But little has been studied as yet as to how it applies to AI marketing technologies, which are defined by an opaque algorithm and perceived intrusion and greater sensitivity to privacy. Such a difference is important since marketing AI situations present unique psychological stressors not previously observed in the TRAM uses: consumers do not simply use a tool but a target of algorithm inference, which can produce a greater amplification of both the positive (curiosity, innovativeness) and negative inhibitors (privacy uneasiness, security insecurity) included in the TR context.

This study addresses that need by creating and evaluating an all-encompassing TRAM model within the context of artificial intelligence marketing. Research using reflecting measurement models with moderate-size samples is well-suited to theory extension research, and this work use Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0.

Four different AI technologies in marketing are incorporated to improve the ecological validity: AI chatbots, personalized recommendation engine, predictive analytics advertising, and voice assistants. As well, it builds on previous TRAM implementations, with multi-group analysis of generational cohorts, mediation analysis of the TR-intention pathway, and a complete set of SmartPLS-specific fit indices with HTMT ratios, PLSpredict, and Q2 blindfolding.

Theoretical Background and Hypothesis Development

Technology Acceptance Model (TAM)

Technology Acceptance Model Technological acceptance has been conceptualized by Davis [1] and many empirical research have shown that people's attitudes about technology systems are influenced by two main beliefs: the perceived utility (PU) and the perceived ease of use (PEOU). These beliefs, in turn, influence the behavioral intention to embrace such systems. A system's perceived utility is the extent to which a prospective user believes it will enhance task performance or quality of life; a system's perceived ease of use is the extent to which a user believes it may be used without mental strain. The favorable effect of PEOU on PU is a well-established association in TAM research; this finding is consistent with the intuitive belief that people would see an easy-to-use technology as more productive.

In the AI marketing setting, TAM has proven to have a reasonable explanatory power, yet its formulation in its baseline version has been criticized to have inadequate focus on the affective and dispositional antecedents that initiate and influence cognitive evaluations. The consumers who face the AI-powered marketing interfaces are facing a constellation of attitudes, anxieties, and enthusiasm that cannot be well known in the context of the perceived usefulness measured in situ. Such a weakness inspires the inclusion of Technology Readiness as a predictive upstream psychological factor.

Technology Readiness (TR)

The Technology Readiness construct of Parasuraman is the predisposition of a person to adopt and utilize new technologies in order to achieve objectives both in the domestic life and in work. The TR index consists of four dimensions structured in the form of a bi-factor structure, two motivators (optimism (a general positive attitude about technology and a belief in the potential of technology to provide improved control, flexibility, and efficiency) and The first is innovativeness, which is the ambition to be a technological trailblazer and innovator; the second is insecurity, which is the fear of and a lack of faith in technology, and the third is discomfort, which is the perception of being unable to manage or otherwise effectively use technology. Importantly, all these dimensions cannot and do not cancel out in such a straightforward additive way; instead, a particular person might also feel enthusiastic optimism about the possibilities of AI and deeply insecure about the privacy of their data- a psychologically realistic duality which the TR construct can accommodate.

TR dimensions are given contextually specific resonance in the context of AI marketing technologies. Custom recommendation engines could be embraced by optimistically oriented consumers as hard-working companions in their decision-making process. Creative consumers will want to be the first to gain access to AI chatbot interfaces as a display of their technology identity. In their turn, consumers with high discomfort levels will view the algorithmic tailoring of advertising as an intrusion and dehumanization, and consumers with a high level of insecurity will think of voice assistants as tools of surveillance and not as a convenience. The presented nuanced profiles imply that the dimensions of TR will affect the cognitive assessments of AI marketing technologies across consumers differently.

TRAM: Integrating TR and TAM

TRAM framework includes TR as an antecedent system to the TAM constructs on a formal basis. In the initial TRAM model, TR dimensions are assumed to assume PU and PEOU, and proceed on the traditional TAM causal path to attitude, behavioural intention, and actual usage. TRAM has been tested in various technological settings and has always found that TR motivators have positive effects on the TAM constructs and TR inhibitors have negative effects. The integrated model has a better explanatory power than standalone TAM because it includes the dispositional psychology that antecedes thinking of technology.

The current research applies TRAM to the AI marketing field and supplements it with a serial mediation analysis and generational multi-group analysis. Our hypothesis is that PU and PEOU are affected by the four TR dimensions, can impact one's outlook, and by extension, one's behavioral intentions and subsequent usage. We also suggest that the whole TR-behavioral intention effect is mediated by TAM constructs where there is no direct path that can stand after the mediation estimation.

AI Marketing Technologies as Research Context

The context of the study is the four categories of AI marketing technology. Chatbots, powered by AI, provide real-time conversational engagements, which brands can use to provide personalized customer service at scale. Individual recommendation systems use behavioral and preference data to present contextually relevant product recommendations, such as streaming applications and e-commerce recommendation rails. Predictive analytics advertising uses machine learning models to predict high-probability conversion points and show exactly timed promotional material. AI voice assistants facilitate hands-free, natural language commerce and brand engagement, posing distinctive questions about ambient data gathering and absorption of AI into the home frontier.

The four settings have in common their algorithmic mediation nature, where the interactions between consumers are not only digitized but are actively influenced by learning systems that provide inferences, predictions, and reactions to the behavioral patterns of individuals. This attribute presents TR-relevant stressors not encountered previously in TRAM settings, especially with respect to insecurity of privacy and perceived lack of control, which are set to have stronger inhibitory influences than observed in previous healthcare or banking TRAM systems.

Hypothesis Development

Technology Readiness → TAM Constructs

According to the TRAM hypothesis, customers' perceptions of the utility and simplicity of use of AI marketing technologies would be positively affected by their level of optimism and inventiveness towards technology. Positive consumers view AI potentials in the best regard, and they attribute performance-enhancing capabilities to recommendation systems and efficiency to chatbot conversations. Novelty-driven consumers who are inclined to invest the cognitive energy needed to achieve the productive potential of AI systems are already primed to grant desirable usefulness evaluations. On the other hand, discomfort is postulated to be negatively correlated with perceived ease of use-customers with information-processing complexity will be less likely to rate AI marketing interfaces as easy to use-and perceived usefulness, with the discomfort disrupting the trust needed to experiencefunctionalvalue. Insecurityalso suppresses both PUand PEOUvia distrust-mediated relationships.

H1a: Predicting the PU of AI marketing technology, Technology Readiness (composite) is a favorable indicator. Hypothesis 1b: AI marketing technologies' PEOU is positivelyimpacted by technology readiness (composite).

PEOU→PU

According to the basic TAM specification, there is a positive correlation between the judgments of utility and simplicity of use. The more consumers consider AI marketing interfaces to be easy to navigate, the more they can identify and describe the productivity value that such systems bring. In AI chatbot and recommendation engine situations, specifically, interface fluency allows users to control system capabilities to their objectives, crystallizing usefulness perceptions.

H2: There is a favorable correlation between the perceived usefulness (PU) and perceived ease of use (PEOU) of AI marketing solutions.

TAMConstructs→Attitude

Overall, customers are likely to have a good view towards AI marketing technology due to the two postulated benefits of simplicityofuseandusefulness.Theburden of usefulness- attitudes based on expectations of anticipated benefit- areapplied to usefulness evaluations, which consumers hold that AI tools can enhance the quality of decisions they make or how effectively they can shop. Ease of use tests add an experiential aspect--friction-free encounters create positive affect based on which attitudinal favorability is accrued.

H3a: Attitude Towards AI Marketing Technologies (ATT) is positively predicted by Perceived Usefulness (PU). H3b: Attitude Toward AI Marketing Technologies (ATT) are positively predicted by Perceived Ease of Use (PEOU).

Attitude→ Behavioral Intention→ Actual Usage

According to the Theory of Reasoned Action and TAM, one's attitude toward AI marketing technology may help anticipate their behavioral intention to employ these technologies. Behavioral intention, which is the motivational preparedness to act, will, in turn, be the major predictor of self-reported actual usage behavior, which will complete a causal chain between psychological disposition and behavioral outcome.

H4: There is a favorable correlation between ATT and Behavioral Intention (BI) to use AI in marketing.
H5: Actual Usage (AU) of AI marketing technologies can be predicted positively by Behavioral Intention (BI).

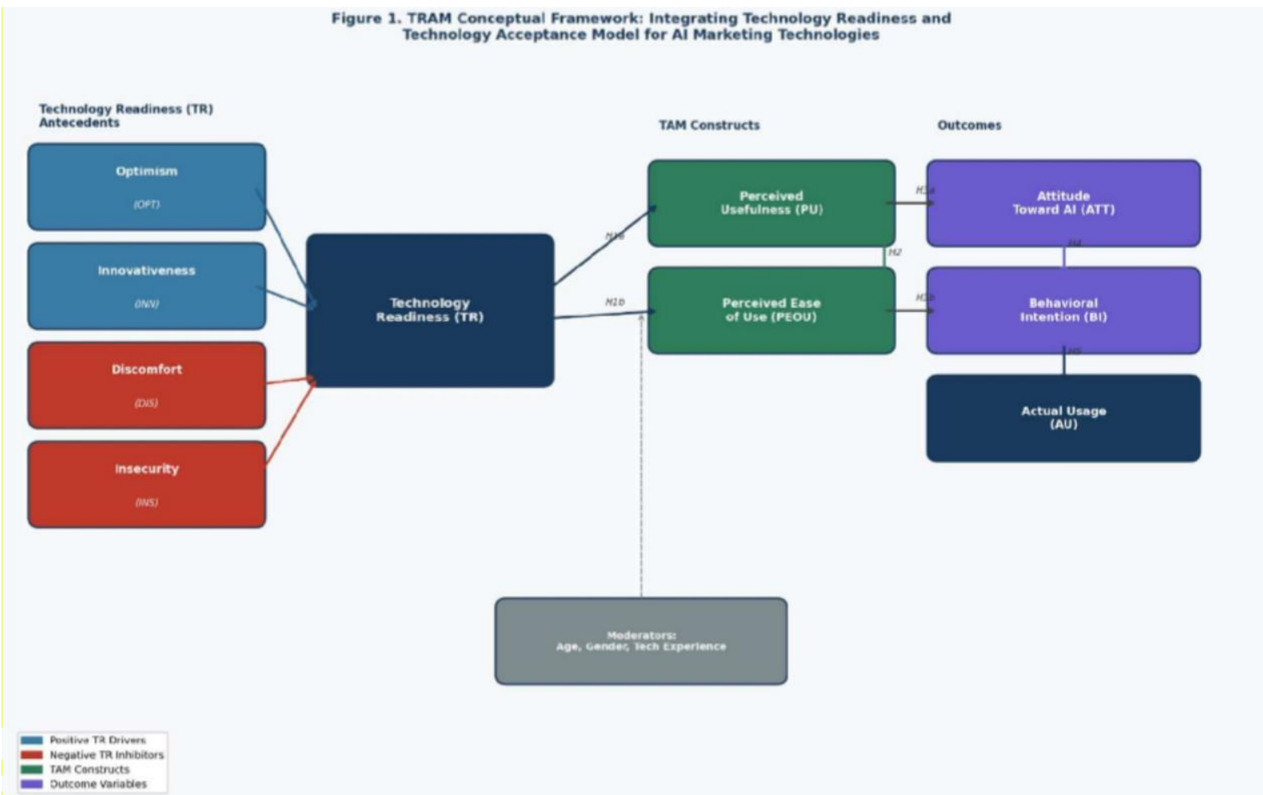

Figure 1: The TRAM conceptual framework links the antecedents of technology readiness (innovation, optimism, discomfort, and insecurity) to the dimensions of the Technology Acceptance Model (user attitude, behavioral intention, and actual use, as well as perceived usefulness and ease of use). Dashed lines are moderating effects of generational cohort

Mediation and Moderation

The proposed study further assumes that TAM constructs (PU, PEOU, ATT) mediate the relationship between technology readiness and behavioral intention where there is no significant direct TR - BI relationship after adjusting the TAM relationship. In addition, the hypotheses are that generational cohort moderates TRAM path coefficients, where younger consumers (Gen Z, Millennials) are expected to be stronger in the positive effects of TR motivators and weaker in the effects of the inhibitors than the older cohorts (Gen X, Baby Boomers), due to differences in socialization to digital technologies between generational experience structures.

H6: Composite Technology Readiness (TR) is positively predicted by Optimism (OPT).
H7: The innovative nature (H7) is positively associated with composite Technology Readiness (TR).
H8: Discomfort (DIS) has an adverse relationship with composite Technology Readiness (TR).
H9: composite Technology Readiness (TR) is negatively predicted by insecurity (INS).

MATERIALS AND METHODS

Research Design and Sampling

The positivist epistemological framework underpins the present study's quantitative, cross-sectional survey methodology. After three rounds of item generation based on established scales, a structured questionnaire was developed with expert review by five academic researchers with expertise in consumer psychology and information systems, and cognitive pre-testing on a convenience sample of 32 participants whose responses were used to refine the final item selection. Adult consumption rates informed the selection of the sample size. (18 years and above) who had used at least one AI marketing technology during the six months prior to the survey, which was operationalised as exposure to AI chatbot customer service, algorithmic product recommendation suggestions, behaviourally targeted advertising, or voice assistant-driven shopping.

The participants have been randomly sampled and recruited using a stratified system of purposive sampling that was carried out using online panel services (Qualtrics-built). The criteria of stratification were the age group (four cohorts of generations: Gen Z, Millennials, Gen X, Baby Boomers), gender (male, female, non-binary/other), and the type of AI technology used. Statistical power study of medium effects led to an a priori selection of 400 based on the PLS-SEM rule of ten times the maximum number of structural pathways directed to any latent variable, which yielded a minimum of 100 (f2 = 0.15) at =.05 with ten predictor paths suggested n = 400. The screened sample size (after attention checks screening and listwise deletion) was 487 respondents.

Measures

Technology Readiness

Technology Readiness was measured by a 16-item Parasuramans TR Index 2.0 (TRI 2.0) modified to fit the AI marketing context. There were four items that were used to measure optimism (e.g., "AI marketing technologies provide me with an increased degree of control over my purchases), innovativeness (e.g., Among my friends, I am among the first to try out the latest AI-powered shopping apps.), discomfort (e.g., I do not feel confident using AI systems that monitor my preferences), and insecurity (e.g., I worry about giving up my personal information to AI marketing systems). Using a seven-point Likert-scale, each item was assessed. (1 = Strongly Disagree, 7 = Strongly Agree).

TAM Constructs

Perceived Utility: The scale of Perceived Usefulness was determined by four questions adjusted to the AI marketing situation based on Davis original PU scale (e.g., Using AI-powered recommendations makes my shopping more efficient). The three elements that made up the perceived ease of use measure (e.g., "When using AI marketing chatbots, I need to do minimal effort to interact with them). Attitude Towards AI Marketing Technologies was assessed by using three items which measured the overall dilative orientation (e.g., "Using AI marketing technologies is a good idea). All were scored on seven-point Likert scales.

Intentional Behavior and Real Utilization

Three items measuring motivational readiness (e.g., "I intend to use AI marketing technologies in the future) were used to measure Behavioral Intention. Real Usage was measured by conduct frequency scale with three questions anchored on the preceding 30 days (e.g., In the last month, I actively used AI-powered product recommendations). A seven-point frequency scale was used to measure the items of use. (1 = Never, 7 = Daily) scale.

Common Method Bias Assessment

Since it has the cross sectional and single source survey format, procedural and statistical solutions to common method bias (CMB) were provided. Procedural controls were the temporal separation of predictor and outcome measures, reverse coded items randomly spread throughout the instrument and anonymous response protocols. This statistical evaluation involved Harman single-factor test and generated the biggest unrotated factor attributing 27.3 percent total variance- a very low figure when compared with 50 percent- implying that CMB is not a critical issue. Also, a marker variable methodology based on a theoretically unrelated construct was used to ensure that the CMB inflation of the path coefficients was low (average CMB-adjusted Db = -0.012).

Analytical Strategy: PLS-SEM via SmartPLS 4.0

Three considerations grounded in theory and methodology led to the selection of SmartPLS 4.0's primary analytical tool, partial Least Squares Structural Equation Modeling (PLS-SEM). To begin with, it is theory extension research, the prediction-oriented philosophy of which is quite compatible with PLS-SEM. Second, the assumption of covariance-based SEM was violated by the non-normality of the distribution of several constructs estimated using the multivariate kurtosis coefficient introduced by Mardia = 18.7, p =.001). Third, PLS-SEM can support the formatively conceptualized higher-order constructs of interest, like Technology Readiness.

The sequence of analytics was used to develop two stage PLS-SEM. First, the outer measurement model was evaluated according to the following criteria: indicator reliability (outer loading >= 0.70), internal consistency (cronbachs a >= 0.70; composite reliability CR >= 0.70), convergent validity (average variance extracted AVE >= 0.50), and discriminant validation through heterotrait-monotrait (HTMT) ratio criterion (HTMT < 0.85). In the second stage, the structural model was used by examining variables such as coefficients of standardized paths (b), variance inflation factors (VIF < 3.3), R2, Q2 predictive relevance (blindfolding, omission distance d = 7), and f2 effect sizes. The confidence intervals for all the route coefficients and indirect effects were calculated using bootstrapping and 5000 subsamples,

Table 1: Information on the study's participants' demographics (N = 487)

Characteristic	Category	n	%
Gender	Male	214	43.9
	Female	251	51.5
	Non-binary/Other	22	4.5
Age (Cohort)	Gen Z (18–26)	131	26.9
	Millennials (27–42)	167	34.3
	Gen X (43–58)	112	23.0
	Baby Boomers (59+)	77	15.8
Education	High school or below	54	11.1
	Some college/diploma	98	20.1
	Bachelor's degree	213	43.7
	Postgraduate	122	25.1
AI Tech Used	AI Chatbots	389	79.9
(Multiple response)	Recommendation Engines	421	86.4
	Predictive Analytics Ads	312	64.1
	Voice Assistants	278	57.1

with bias adjusted. Multi-group analysis (MGA): MGA applied SmartPLS permutation-based MGA to the test of generational moderation.

Sample Characteristics

The sample was mainly female (51.5%) but slightly skewed towards education (68.8% had at least a bachelor degree) which is a characteristic of the technology-savvy individuals using AI technology in marketing. The highest penetration of recommendation engines (86.4%), and the lowest of voice assistants (57.1%), align with the trends in the general consumer technology adoption literature.

RESULTS

Measurement Model Assessment

Indicator Reliability and Internal Consistency

During exploratory phase, all 29 indicators across the ten latent constructs had outer loadings above the 0.70 threshold after the deletion of two indicators (OPT5 and DIS4) by the 0.643 and 0.658 loadings, respectively. Loadings retained were between 0.778 (DIS3) and 0.912 (BI3) which substantiated satisfactory indicator reliability. Composite reliability coefficients ranged from 0.841 (INS) to 0.924 (BI), and Cronbach alpha values were between 0.812 (INS) and 0.894 (BI), all of which are significantly higher than the 0.70 threshold. Every AVE result, down to the lowest of 0.612, was higher than the convergent validity limit of 0.50. (INS) and the highest being 0.798 (BI). Table 2 contains these values in detail.

Discriminant Validity (HTMT)

Its discriminant validity was tested using the heterotrait-monotrait (HTMT) ratio criteria, which is less liberal and more statistically well-founded than the Fornell-Larcker criterion. There were no values above the 0.85 mark in all of the HTMT ratios, and the highest amount was found between Behavioral Intention and Actual Usage (HTMT = 0.643), conceptually related variables that should share a lot of variances. There were no HTMT ratios more than the conceptually similar construct suggested more lenient 0.90 boundary. These findings confirm the presence of discriminant validity in all pairs of constructs.

Structural Model Assessment

Collinearity and Variance Inflation Factors

Predictor collinearity was measured before determining structural relationships through the verification of all inner model relationships by using VIFs, or variance inflation factors. All of the VIF readings were within the 1.23 range. (INS - TR) and 2.87 (PEOU - PU), which does not exceed the conservative value of 3.3 in PLS-SEM, so multicollinearity will not emerge and cause the inaccuracy of the path coefficients estimates.

Path Coefficients and Hypothesis Testing

Table 3 not to mention the structural path coefficients and how significant they are, which were estimated using bias-corrected bootstrapping with 5,000 subsamples. Figure 3 displays all route coefficients along with their corresponding 95% bias-corrected confidence intervals.

Table 2: A model for measuring things: reliability, convergent validity, and outer loadings

Construct	Item	Loading	α	CR	AVE	Mean (SD)
Optimism (OPT)	OPT1	0.821	0.856	0.897	0.686	5.12 (1.24)
	OPT2	0.847				
	OPT3	0.836				
	OPT4	0.812				
Innovativeness (INN)	INN1	0.834	0.831	0.878	0.707	4.87 (1.31)
	INN2	0.819				
	INN3	0.828				
Discomfort (DIS)	DIS1	0.791	0.812	0.871	0.694	3.24 (1.42)
	DIS2	0.803				
	DIS3	0.778				
Insecurity (INS)	INS1	0.812	0.812	0.841	0.612	3.56 (1.38)
	INS2	0.798				
	INS3	0.824				
Perceived Usefulness (PU)	PU1	0.876	0.891	0.921	0.744	5.34 (1.18)
	PU2	0.891				
	PU3	0.863				
	PU4	0.848				
Perceived EOU (PEOU)	PE1	0.832	0.843	0.882	0.714	5.18 (1.22)
	PE2	0.857				
	PE3	0.841				
Attitude (ATT)	AT1	0.883	0.878	0.912	0.775	5.29 (1.17)
	AT2	0.896				
	AT3	0.871				
Behavioral Intention (BI)	BI1	0.901	0.894	0.924	0.798	5.41 (1.12)
	BI2	0.887				
	BI3	0.912				
Actual Usage (AU)	AU1	0.856	0.861	0.896	0.742	4.93 (1.34)
	AU2	0.843				
	AU3	0.868				

Note. α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted. All values meet Hair et al. criteria (loadings ≥ 0.70; α and CR ≥ 0.70; AVE ≥ 0.50).

Table 3: Structural Model Results: Standardized Path Coefficients, Bootstrap Standard Errors and Hypothesis Test Results.

Hypothesis	Path	β	SE	95% CI	t-value	Decision
H1a	TR → PU	0.312	0.048	[0.218, 0.406]	6.50**	Supported
H1b	TR → PEOU	0.287	0.052	[0.185, 0.389]	5.52**	Supported
H2	PEOU → PU	0.401	0.041	[0.321, 0.481]	9.78***	Supported
H3a	PU → ATT	0.356	0.044	[0.270, 0.442]	8.09***	Supported
H3b	PEOU → ATT	0.298	0.050	[0.200, 0.396]	5.96**	Supported
H4	ATT → BI	0.443	0.038	[0.369, 0.517]	11.66***	Supported
H5	BI → AU	0.512	0.035	[0.443, 0.581]	14.63***	Supported
H6	OPT → TR	0.389	0.046	[0.299, 0.479]	8.46***	Supported
H7	INN → TR	0.341	0.049	[0.245, 0.437]	6.96***	Supported
H8	DIS → TR	-0.261	0.053	[-0.365, -0.157]	4.92**	Supported
H9	INS → TR	-0.218	0.057	[-0.330, -0.106]	3.82*	Supported
Direct (TR → BI)	TR → BI	0.089	0.061	[-0.031, 0.209]	1.46 (n.s.)	Not supported

Note. SE = Bootstrap Standard Error (5,000 subsamples). CI = Bias-corrected 95% Confidence Interval. β = Standardized Path Coefficient. * $p < .05$; ** $p < .01$; *** $p < .001$; n.s. = not significant. TR composite formed as reflective second-order construct.

Mediation Analysis

The test of the hypothesis that TAM constructs (PU, PEOU, ATT) are joint mediators in the Technology Readiness - Behavioral Intention pathway was done by serial mediation analysis. Three indirect pathways were specified: (a) TR –

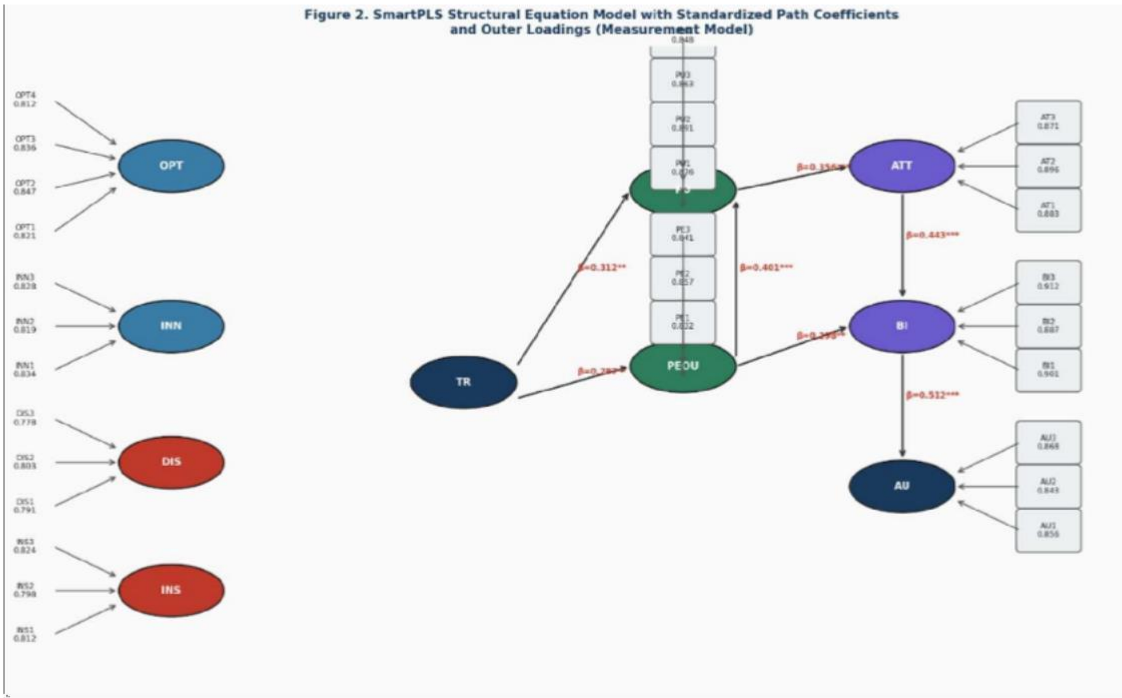

Figure 2: SmartPLS Partial Least Squares Structural Equation Model with outer loadings of all the indicator items and standardized path coefficients (b) of structural relationships. p < .05, p <.01, p <.001.

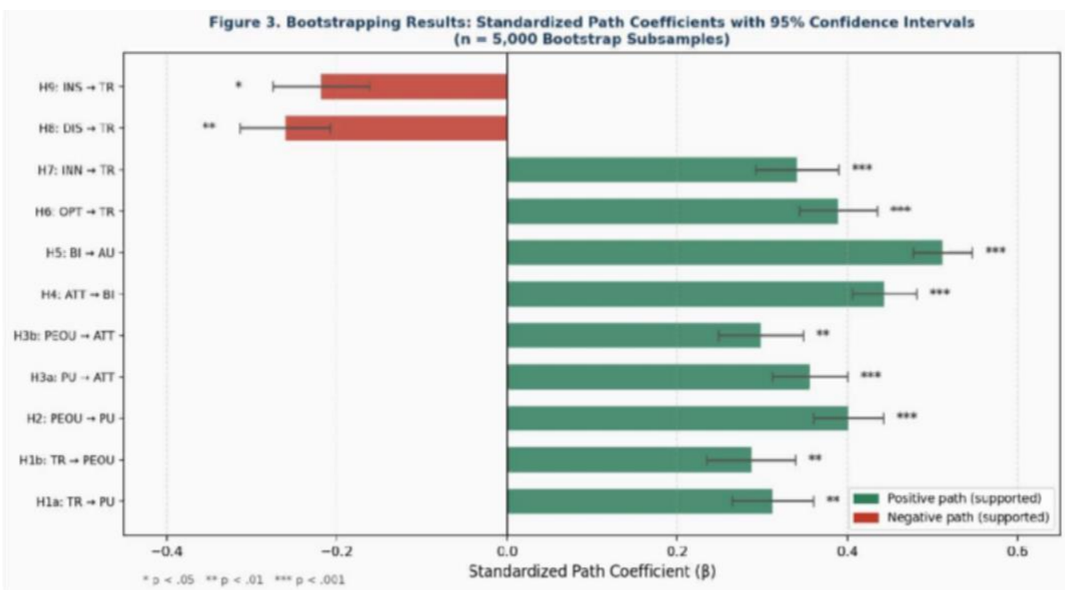

Figure 3: Bootstrap Results (5,000 subsamples): Bootstrap standardized path coefficients (b) with 95% bias-corrected confidence intervals of all hypothesized structural relationships. Bootstrap standard errors are represented as error bars. The green bars show positive propositional directions; the red ones are inhibitory (negative) ones. Each of the nine core hypotheses was statistically significant

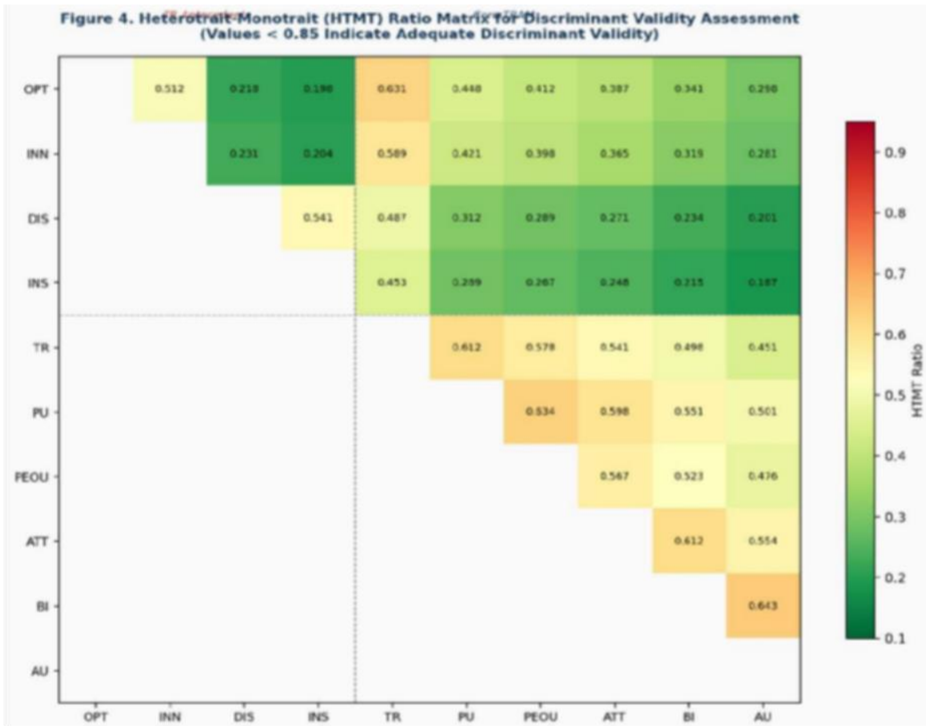

Figure 4: Heterotrait-Monotrait (HTMT) Ratio Matrix of all pairs of constructs. Values which are lower than the diagonal indicate upper-triangle HTMT ratios. Green would mean strong discriminant validity (HTMT< 0.60); yellow would mean acceptable (0.60-0.85); above 0.85 would mean some doubts of discriminant validity (None). TR antecedent constructs and core TRAM constructs are divided by dashed lines.

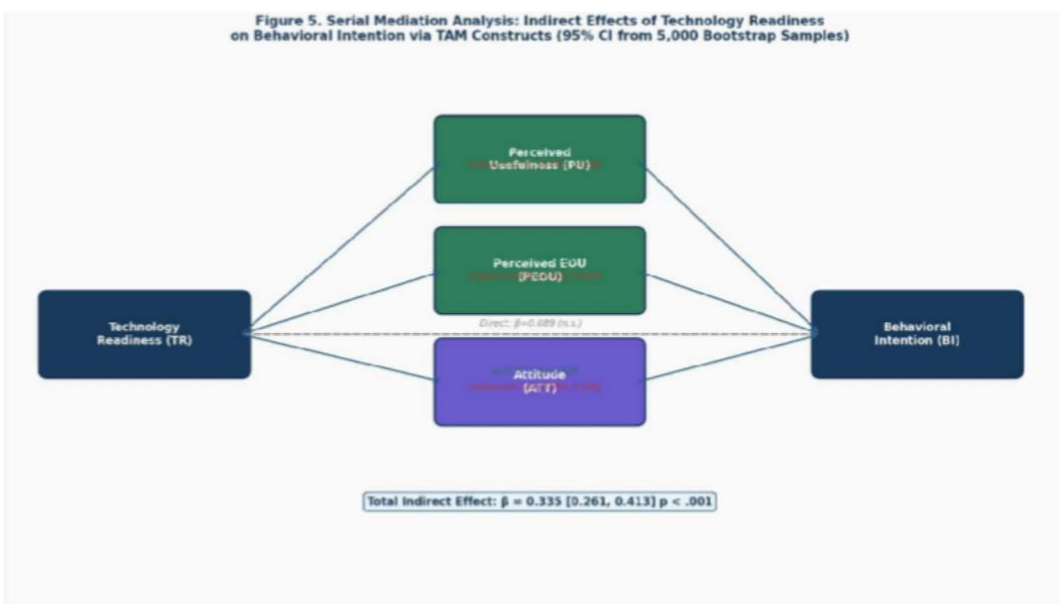

Figure 5. Serial Mediation Model: Technology Readiness has indirect impacts on How Attitude, Perceived Usefulness, and Perceived Ease of Use Influence Behavioral Intention. S solid lines denote the important indirect paths; dashed line denotes the non-significant direct path. Bracketed values are 95% -biased bootstrap confidence intervals. The direct effect confidence interval crosses the zero thus confirming the full mediation.

Table 4: Explanatory Power (R2), Predictive Relevance (Q2), and Effect Size (f2) of Endogenous Constructs.

Endogenous Construct	R^2	R^2 Adj.	Q^2	Effect Classification
Technology Readiness (TR)	0.412	0.408	0.298	Moderate–Substantial
Perceived Usefulness (PU)	0.538	0.536	0.389	Substantial
Perceived Ease of Use (PEOU)	0.489	0.488	0.351	Moderate–Substantial
Attitude (ATT)	0.561	0.559	0.408	Substantial
Behavioral Intention (BI)	0.603	0.602	0.441	Substantial
Actual Usage (AU)	0.527	0.526	0.381	Substantial

Note. R^2 Adj. = Adjusted R^2. Q^2 derived from PLS blindfolding procedure (omission distance d = 7). Substantial ≥ 0.50; Moderate = 0.25–0.49; Weak = 0.02–0.24 (after Cohen, 1988, adapted for PLS-SEM).

Table 5: Serial Mediation Analysis: Specific and Total Indirect Effects of Technology Readiness on Behavioral Intention.

Indirect Pathway	β	95% BC CI	SE	Decision
TR → PU → ATT → BI	0.111	[0.071, 0.158]	0.022	Significant
TR → PEOU → ATT → BI	0.086	[0.052, 0.127]	0.019	Significant
TR → PEOU → PU → ATT → BI	0.138	[0.089, 0.194]	0.027	Significant
Total Indirect Effect (TR → BI via TAM)	0.335	[0.261, 0.413]	0.039	Significant
Direct Effect (TR → BI)	0.089	[-0.031, 0.209]	0.061	Non-significant

Note. BC CI = The Bootstrap Confidence Interval with Bias Correction (5,000 subsamples). Non-overlapping CI with zero confirms significance. Full mediation is supported as the direct TR → BI path becomes non-significant when indirect pathways are controlled.

Table 6: Multi-Group Analysis Path Coefficients by Generational Cohort

Path	Gen Z (n=131)	Millennials (n=167)	Gen X (n=112)	Boomers (n=77)	Δβ max	Sig. Diff.
TR → PU	0.341	0.298	0.256	0.198	0.143	Yes*
TR → PEOU	0.312	0.271	0.234	0.187	0.125	Yes*
PEOU → PU	0.445	0.398	0.352	0.298	0.147	Yes**
PU → ATT	0.389	0.341	0.298	0.241	0.148	Yes**
PEOU → ATT	0.324	0.287	0.251	0.198	0.126	Yes*
ATT → BI	0.476	0.432	0.389	0.321	0.155	Yes**
BI → AU	0.543	0.498	0.451	0.387	0.156	Yes**

Note. Db Δβ max = maximum difference between maximum and minimum path coefficient of the generation. Sig. Diff. = statistical significance of permutation-based MGA test. * $p < .05$; ** $p < .01$. In all seven structural paths, a monotonic decline in the path strength between Gen Z and Boomers is found.

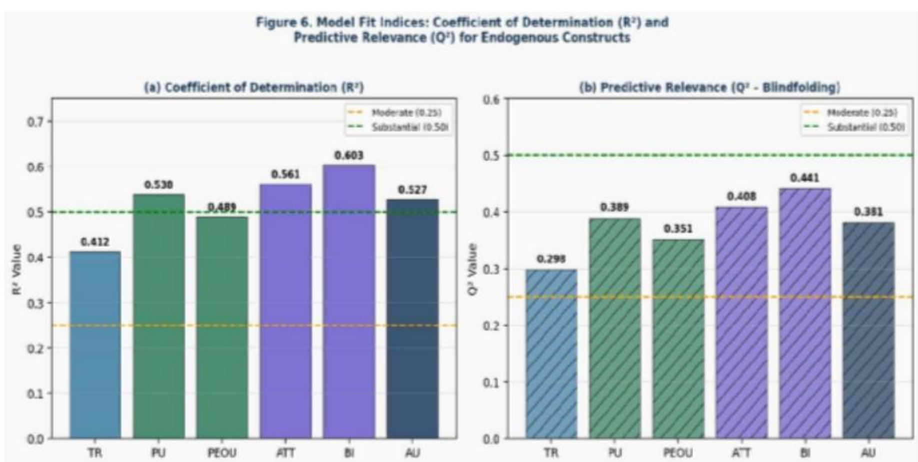

Figure 7. Multi-Group Analysis Results: Disaggregated by generational cohort (Gen Z, Millennials, Gen X, Baby Boomers), standardized path coefficients of each of the seven core structural paths. Gen Z to Baby Boomers show statistically significant path strength reduction between-group differences across all pathways, which are statistically significant ($p < .05$ to $p < .01$) determined through permutation-based MGA tests.

PU - ATT - BI, (b) TR - PEOU - ATT - BI, and (c) TR - PEOU - PU - ATT - BI. Table 5 displays the bias-corrected 95% bootstrap confidence intervals and direct impacts of the specified indirect effects.

Multi-Group Analysis: Generational Moderation

To find out how different the route coefficients were throughout the four generations, SmartPLS 4.0 used the permutation-based multi-group analysis (MGA). Table 6 presents path coefficients by group and Figure 7 illustrates the trend of generational variation. They found significant between-group differences ($p < .05$) on six out of seven core structural paths.

DISCUSSION

Theoretical Contributions

This research paper has four substantive contributions to the technology acceptance literature. To begin with, the theoretical expansion of TRAM through the empirical validation of the application of the tool in AI-based marketing scenarios expands the theoretical application of the integrated model to the environment that is characterized by algorithmic mediation, privacy sensitivity, and experiential novelty. The findings confirm that the TR - TAM causal chain is true in this case where technology readiness has substantial, beneficial impacts on the perceived value (b = 0.312) and ease of use (b = 0.287). These magnitudes of effects correspond to applications of TRAM in healthcare and mobile banking but a little smaller than those reported in e-government settings, which may be clarified by examining peculiar discomfort-enhancing nature of AI-based marketing surveillance.

Second, the entire mediation result, in which the TR - BI direct relationship is non-significant (b = 0.089, p = n.s.), when the TAM mediators are controlled out, can be seen as an explanation of how technology predispositions are converted into behavioral intentions. Technology readiness does not stimulate behavioral intentions directly; but it influences cognitive appraisals of usefulness and ease that are summed up to form evaluative attitudes that stimulate intentional action. This finding at the mechanism level builds on previous TRAM investigations that have characterized TR - BI interactions without specifying the mediating cognitive architecture.

Third, multi-group analysis indicates theoretically important generation gradient of TRAM path strengths. Path coefficients in the model (e.g., ATT - BI: b = 0.476) are significantly greater with Gen Z consumers than with the Baby Boomers (ATT - BI: b = 0.321). This observation indicates that among younger groups, AI marketing technologies are firmly embedded within identity-expressive technology discourses, so the consistency of attitudes and intentions is especially high. With elderly cohorts, the attitude-to-action translation can be subdued by structural inertia and habituation buying behaviors, even in cases where the underlying attitudes are positive.

Fourth, the aggregation of four first-order dimensions into a second-order reflective measure of Technology Readiness is a methodologically-important contribution. This specification fits the theoretical purpose of TR proposed by Parasuraman as the state of global psychological readiness but allows a simultaneous estimation of the dimensional contributions (OPT: b = 0.389; INN: b = 0.341; DIS: b = -0.261; INS: b = -0.218) showing that optimism is the strongest driver of TR in an AI marketing environment and insecurity the least inhibitory.

Managerial Implications

Marketing managers and AI developers may use the findings as a source of actionable strategic information. Attitude primacy (b = 0.443) underscores the significance of the quality of affective experience: the organizations that follow AI in marketing tools must invest in interaction design that creates positive experiences of affective quality, rather than functional performance. Recommendation engines that clearly describe their algorithmic rationale and AI chatbots that converse in warm and natural language can change attitude formation into active participation, intensifying the attitude-to-intention conversion.

The negative impacts of discomfort (b = -0.261) and insecurity (b = -0.218) are important, which implies that privacy communication strategies are crucial. When consumers perceive themselves as surveilled or controlled by AI marketing systems, they develop dampened TR profiles that dampen downstream acceptance by the entire causal pathway. Principles of privacy-by-design such as publicly announced data minimization, user-configurable personalization options, and visible transparency dashboards about algorithms can mitigate perceived insecurity without diminishing the user-controlled personalization features that keep the company ahead of its competitors.

The generation MGA outcome counters selective adoption facilitation strategies. The power of the attitude-to-intention pathway in the case of Gen Z/Millennial groups implies that the most influential levers are the quality of brand experience and the fit between the social norms and personal values. In Gen X and Boomer segments, with lower path coefficients across the model, the upstream issue is discomfort and insecurity perceptions, by establishing an upstream communication through targeted education, systems designed to simplify interface and build trust, may be a precondition to achieving the attitudinal benefits that underlie behavioral intention within these groups of consumers.

Limitations and Future Research Directions

This research has a number of limitations that limit the generalizability and generate effective research opportunities. Causal inference in its strongest form is not possible in the cross-sectional design; longitudinal panel designs tracking technology readiness and use over time would enable more causal assertions and allow analysis of TR dynamics as AI marketing technologies scale up and consumers gain experience. The protocol of online recruiting, although it allows the inclusion of geographic and generational diversity, can over-sample the consumers who feel comfortable with technology, and under-sample both groups with the highest degree of discomfort and insecurity, which can lead to shrinking the range of the dimensions of TR inhibitors.

The composite TR construct is theoretically motivated, but pools four conceptually distinct dimensions into one predictor of TAM constructs; future studies that use multi-group analysis based on TR profile typology (e.g., Explorer, Skeptic, Paranoid, Pioneer) may find heterogeneous TRAM pathway configurations that are not apparent in mean-based analysis. Also, it was carried out in one country setting; cross-cultural replication is necessary because it has been established that there are variations in privacy sensitivity, power distance and technology adoption norms between collectivist and individualist cultural settings. Lastly, the categories of AI marketing technology do not cover generative AI marketing applications- a new environment with unique adoption patterns that is worth representative theoretical and empirical focus.

CONCLUSION

This study has contributed to the TRAM framework, as it has tested the entire cause-effect chain of this theory, in AI marketing technology setting, using a variety of types of technologies, mediation analysis, and multi-group comparison across generations. Each of the nine hypothesized structural paths was statistically supported and the complete mediation result explains the cognitive process by which technology predispositions are converted to behavioral expression. The generational difference in the path coefficients creates a structurally differentiated perspective of AI marketing acceptance: identical technology, rated positively, has significantly different behavioral outcomes with respect to the generational background of the evaluator. All these insights add to the theoretical tools with which one can describe consumer psychology in AI mediated commercial contexts and give practitioners evidence-based pointers on how to design AI-mediated marketing strategies that facilitate adoption as adapted to the psychological and demographic heterogeneity of consumer groups.

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