IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Decoding Consumer Intentions: The Role of Trust and Consciousness in AI-Driven Marketing Using TAM

Pranjay Bajaj, Abhishek Pathak
Student 2nd Year PGDM, Student 2nd Year PGDM
PGDM,
Management Development Institute, Gurgaon, India

Abstract : This report examines the influence of artificial intelligence (AI) on consumer decision-making through the Technology Acceptance Model (TAM), focusing on how companies can better communicate their AI-enabled digital products. As AI becomes a key driver of brand engagement, understanding consumer perceptions of trust, perceived usefulness, and awareness is critical for influencing purchase intentions and behavior. Using survey data and TAM constructs, this study identifies how trust in AI-generated content and consumer consciousness of AI technologies directly affect attitudes toward AI products, ultimately shaping purchase decisions. Key insights include the importance of clear, transparent communication and emphasizing the functional benefits of AI-driven products. The findings offer actionable recommendations for companies to strategically communicate AI technologies in ways that enhance consumer trust and drive engagement. These recommendations are designed to aid businesses in aligning their digital product messaging with consumer expectations, thereby influencing decision-making and fostering adoption. Limitations and future research directions are discussed to expand the practical applications of AI in digital marketing.

1.INTRODUCTION

Over time, technology has consistently been essential to maintaining the brand's relevance. As technology has been more widely used, some brands have sought to take advantage of this development to improve user experience and, in turn, attempt to sway consumer behavior. Among the more prominent examples of such technology are chatbots and artificial intelligence. AI technologies are being used increasingly to automate tasks that require a lot of human labor, like content creation, customer service, and data analysis. (Smith, 2020). By integrating technology into their applications and storefronts, brands want to both engage and deliver convenience to their customers by creating a simple, engaging environment. Numerous big corporations, including Nike and Adidas, have embraced this concept.

The impact of technology on consumer thought processes in the marketing industry, particularly in retail, has been extensively studied (Singh & Thirumoorthi, 2019). AI's influence on customer behavior, particularly in e-retailing, has been a focal point, emphasizing its user-friendly nature and enhancing customer knowledge of its application in the e-commerce sector (Bhagat et al., 2022). The manner that brands have started to promote themselves has changed along with the customer experience. Personal health care is a prime business to gauge public confidence in artificial intelligence (AI) and other cutting-edge technologies. To do this, we must observe how people accept lifestyle decisions and equipment that is monitored by AI (Kyung & Kwon, 2022).To improve brand engagement, managers should focus on three key aspects of artificial intelligence: accessible, interactive, and dynamic (Hermann et al., 2023). The study investigates how brand engagement in digital marketing efforts could be enhanced by augmented reality (AR). It investigates how consumers perceive and engage with augmented reality (AR) experiences, showing a positive relationship between brand interaction and consumers' evaluations of AR interactions. The findings demonstrate that augmented reality (AR) has the ability to dramatically affect consumer engagement and purchase intent, especially in younger and lower-income demographics.

Important areas of research in any sector include the disclosure of AI's role in brand communication and its effects on perceptions of brand sentiment and authenticity. With AI-generated content becoming more and more common in marketing campaigns, there is a growing interest in understanding how consumers interpret it and whether identifying AI as the producer influences their opinions and actions. In response to early doubts about the veracity and authenticity of content produced by artificial intelligence, researchers are examining the impact of transparency on consumer trust and brand perception. A recent study shows that individuals do not always find a brand's voice to be emotive or genuine when AI is identified as the author of a document (Chen & Lee, 2023). Indeed, some data suggests that consumers would be open to receiving AI-generated material if they think it is pertinent, useful, and consistent with the brand's identity and core values. These results highlight the potential advantages of artificial intelligence (AI) in marketing. Additionally, research has examined the profound impacts of AI on consumer experiences and brand preferences in the banking industry. This illustrates how AI-driven initiatives can provide distinctive qualities and transform brand interactions

(Ho & Chow, 2022). After that, the study turns to the rapidly developing subject of artificial intelligence speech, delving into the nuances of how people perceive similarity and the positive impacts it has on attachment, perceived interaction, and intention to buy (Kim et al., 2022).

Despite progress, critical gaps remain in our understanding of the marketing effectiveness of developing technologies, notwithstanding improvements. "Exploring the Effectiveness of Augmented Reality in Enhancing Brand Engagement: A Study of Digital Marketing Strategies," a 2023 report on augmented reality marketing concedes the need for further research to fully grasp its impact and optimization. Similarly, research on AI intervention's comparability with human intervention lacks comprehensive theoretical frameworks and mediating variables (Chen et al., 2023). Furthermore, greater research across industries and demographics is required due to the increasing usage of AI in influencer marketing (Sands et al., 2022). Additionally, although AI meets the needs of brands, it is also playing a bigger and bigger role in meeting the needs of consumers, as demonstrated by chatbots (Cheng & Jiang, 2021).

Comprehending user feedback on assessments generated by artificial intelligence systems is essential for comprehending modern-day consumer behaviour. Our study, led by Lopez & Garza (2023), explores topics such as transparency and trust in order to clarify how people engage with AI systems. In particular, using the Technology Acceptance Model (TAM) as a framework, our study attempts to investigate the complex linkages that exist between consumer behaviour toward AI-generated content, trust, and consciousness. We want to provide insight into the emotional variables impacting consumers' purchase intention and behavioural intention to use AI-generated content by studying how they perceive and interact with it. By conducting a thorough analysis that covers trust, consciousness, perceived usefulness, and simplicity of use, our research aims to identify the psychological mechanisms that support consumers' reactions to marketing efforts that use artificial intelligence.

Our work aims to close the gap between logical decision-making processes and emotional components of consumer behaviour by extending the TAM model. By adding emotional elements like trust and consciousness to the TAM framework, we recognize the complexity of consumer-brand relationships in the digital era. With the market becoming more and more AI-driven, this strategy seeks to give marketers insightful information to help them optimize their approaches. Furthermore, by connecting these variables to real purchase behaviour, our research hopes to further knowledge of the affective aspects driving behavioural intents to use AI-generated content as well as buy intentions. By reorienting the focus from rational decision-making processes to the emotional dimensions of consumer behaviour, this innovative methodology enhances earlier research.

2. LITERATURE REVIEW

The literature reviewed emphasizes the integration of emotional elements, particularly trust and consciousness, into the Technology Acceptance Model (TAM) to assess artificial intelligence's (AI) impact on consumer behaviour. Trust is a focal point in the advanced TAM framework, indicating how AI's accuracy when presenting numerical data enhances belief and positive intentions for actions of consumers consequently affecting their acceptance of AI technologies (Kim et al., 2021). This is modification acknowledged the extent to which consumers carry on interpersonal transactions with AI beyond ease of use to emotional involvement and psychological responses towards AI systems. Research has shown that credibility of artificial intelligence is pivotal in shaping consumer experiences hence need for AI systems that are not only accurate but also communicates its findings transparently in order to gain trust (Khan & Mishra, 2024). Also, hashing consciousness into TAM shows how much consumers knows about ethical issues related to AI technology since it is believed by some scholars that more conscious consumers perceive AI's functional benefits as ethically inappropriate (Khrais, 2020). The relationship is critical as it determines whether or not a consumer will use an artificial intelligence-powered product or service.

Additionally, this can be seen from studies conducted by Davenport et al. (2019) and Deng et al. (2019), who found out that even though personalization through AI might have great effects on consumer behavior there is need to maintain customer trust specifically in terms of data utilization while customizing customer experience. It cannot be gainsaid that explainable AI (XAI) plays a big role in this respect, as it caters for the request made by customers on transparent and understandable operations of AIs so as to build trust among them. (Khrais, 2020).

Consequently, including such emotional aspects like trust and consciousness would lead to a complete understanding of how AI influences customer behavior using TAM model. It does not only recognize usability and ease-of-use as important but also emphasizes the emotional and moral dimensions associated with accepting technological advancements. This calls for further research into this expanded model addressing the interaction between these emotions aspects with traditional TAM variables regarding consumer acceptance or usage of AI. In this way, we will be able to understand the relationship between consumer and AI better and be provided with relevant insights for marketing and consumer research participants in academia and industry.

Now we are going to substantiate pair-wise construct and conclude to draw our Direct and Indirect hypotheses. We will also discuss why the particular hypothesis that we have drawn is important and interesting.

3. PROPOSED MODEL

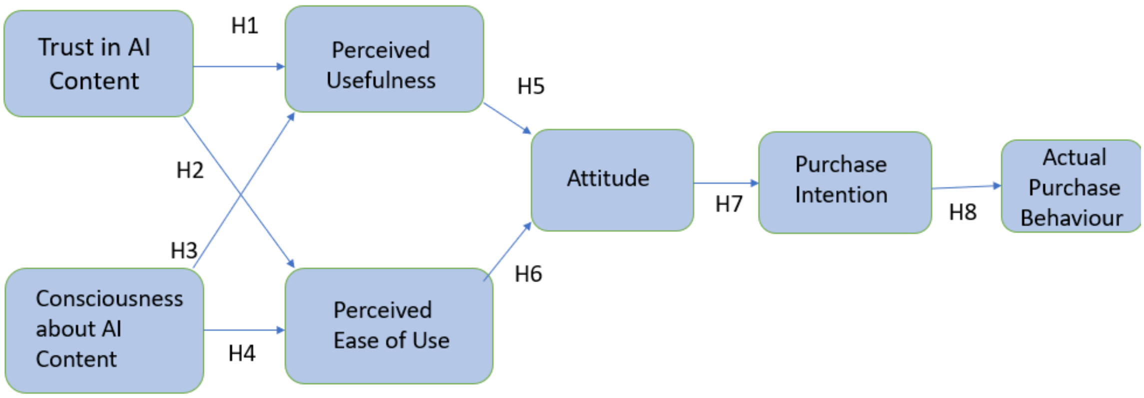

Figure 1: Diagram of Theoretical Model

3.1 List of Hypotheses

Trust Hypotheses:
- H1: Trust in AI content positively influences consumers' perceived usefulness of the AI brand content.
- H2: Trust in AI content positively influences consumers' perceived ease of use of the AI brand content

Consciousness Hypotheses:
- H3: Consciousness about AI content positively influences consumers' perceived usefulness of the AI brand content.
- H4: Consciousness about AI content positively influences consumers' perceived ease of use of the AI brand content

Perceived Usefulness Hypothesis:
- H5: Perceived usefulness of the AI brand content positively influences consumers' attitude towards using it.

Perceived Ease of Use Hypothesis:
- H6: Perceived ease of use of the AI brand content positively influences consumers' attitudes towards using it.

Attitude Hypothesis:
- H7: Consumers' attitude towards using the AI brand content positively influences their purchase intention.

Purchase Intention Hypothesis:

H8: Consumers' purchase intention towards using the AI brand content positively influences their actual purchase behavior.

4. METHODOLOGY SECTION

4.1 Scale Measurement

In this study, several constructs were measured using established scales adopted from previous research. Trust in AI was assessed using a scale consisting of 5 items, adapted from the work of Bleier et al. (2019). Consciousness was evaluated through a 7-item scale derived from the study by Shahzad et al. (2024). Perceived usefulness was measured using a 7-item scale based on the instrument developed by Davis (1989). Perceived ease of use was assessed with a 7-item scale adapted from Fu et al. (2016). Attitude was measured using a 5-item scale drawn from Kirkby et al. (2023). Purchase intention was evaluated using a 5-item scale adopted from Venkatesh et al. (2003). Finally, actual purchase behavior was assessed using a 5-item scale adapted from Wee et al. (2014). All scales utilized a Likert scale ranging from 1 to 7, allowing participants to indicate their agreement or disagreement with each item. These scales were selected based on their reliability and validity in previous studies, ensuring the robustness of the measurement approach in this research.

4.2 Questionnaire Set

1.Construct: Trust in AI content (Bleier et al.,2019)
1. I feel very confident about AI's abilities
2. AI appears to be well-qualified in the area of e-commerce.
3. AI appears to try hard to be fair in dealing with others.
4. I like AI's values.
5. Sound principles seem to guide AI's behavior.

2.Construct: Consciousness/ Awareness (Shahzad et al. , 2024)
1. I possess knowledge about the use of AI applications.
2. The experience using AI-enabled shopping has been great
3. I follow the news about AI
4. I discuss AI with people around me.
5. I understand AI.
6. I read about the issues of AI.
7. I follow the developments of AI.

3.Construct: Perceived Usefulness (Davis, F. D. ,1989)
1. My job would be difficult to perform without AI.
2. Using AI gives me greater control over my shopping
3. Using AI saves me time
4. AI enables me to accomplish tasks more quickly.
5. Using AI reduces the time I spend on unproductive activities
6. Using AI improves my shopping performance
7. Using AI improves the quality of the shopping I do

4. Construct: Perceived Ease of Use(Fu et al. 2016)
1. I find the AI easy to use.
2. I find it easy to get the AI to do what I want it to do
3. Interaction with the AI is difficult.
4. The AI is flexible to interact with.
5. It is easy for me to remember how to perform tasks using the AI.
6. Learning to operate the AI is easy for me.
7. My interaction with the AI is clear and understandable.

5.Construct: Attitude (Kirkby et al . , 2023)
1. I find the AI appealing
2. I find the AI good
3. I find the AI pleasant
4. I find the AI favourable
5. I find the AI likable

6.Construct: Purchase Intention (Venkatesh et al., 2003)
1. Describe your overall feeling about the AI-enabled purchase
2. Do you intend to buy through AI-enabled means
3. You have a high purchase interest through AI-enabled means.
4. You are definitely buying through AI-enabled mode
5. You will probably buy using AI-enabled means

7. Construct: Actual Purchase Behaviour (Wee et al., 2014)
1. I often buy products suggested by AI
2. I would buy products suggested by AI in the near future
3. I often buy products suggested by AI on regular basis.
4. I often buy products suggested by AI due to its ease.
5. I often buy products suggested by AI due to its usefulness.

4.3 Sampling Design

For this study, a sample size of 277 responses was determined to achieve adequate statistical power and representativeness for the research objectives. Surveys were utilized as the primary data collection method, allowing for efficient gathering of data from a diverse range of participants. The sampling method employed was convenience sampling, wherein participants were recruited based on their availability and willingness to participate in the study. This approach was chosen for its practicality and feasibility within the study's timeframe and resource constraints. The sampling frame comprised individuals who had access to the survey platform utilized for data collection. It's worth noting that while convenience sampling may introduce some limitations regarding generalizability, efforts were made to ensure diverse representation within the sample to mitigate potential biases. Overall, the selected sample size and sampling method were deemed appropriate for addressing the research questions and objectives of the study. The following contains the demographic information of the frame sample.

Row Labels	Sum of Frequency
Female	95
Male	181
Grand Total	**276**

Figure 2: Demographic Information – Gender Distribution

:

Row Labels	Female	Male	Grand Total
Bachelor’s degree or equivalent	38	79	117
Doctoral	5	4	9
Masters	48	84	132
Professional qualification	3	12	15
School	1	2	3
Grand Total	**95**	**181**	**276**

Figure 3: Demographic Information – Educational Qualification

Row Labels	Female	Male	Grand Total
<30	78	148	226
>60	1	5	6
30-40	6	14	20
40-50	4	7	11
50-60	5	6	11
51-60	1	1	2
Grand Total	**95**	**181**	**276**

Figure 4: Demographic Information – Age

Row Labels	Female	Male	Grand Total
Central	5	9	14
East	6	14	20
North	56	96	152
North East		3	3
South	12	40	52
West	16	19	35
Grand Total	**95**	**181**	**276**

Figure 5: Demographic Information – Regional Distribution

4.3.1 Demography of Participants

The demographic characteristics of the participants are summarized as follows:

Gender: The majority of respondents were male (65.6%), followed by female respondents (34.4%).
Age: The age distribution of participants varied, with the majority falling in the age range of <30 (81.8%), followed by 30-40 (7.2%).
Educational Qualification: Participants represented diverse educational backgrounds, with the highest proportion holding a Master's degree (47.8), followed closely by those with a Bachelor's degree or equivalent (42.3%).
Geographic Location in India: Participants were distributed across various geographic regions in India, with the highest proportion from the North (55.07%), followed by the South (18.9%) and West (12.6%).

4.4 Reliability Measure

The reliability test, often assessed using Cronbach's alpha, is crucial for ensuring that the items in a questionnaire or scale produce consistent and dependable measurements of the intended constructs. A Cronbach's alpha value greater than 0.7 is generally considered indicative of good reliability, although researchers should interpret this threshold in the context of their specific study and measurement instrument. In our case the items in the construct strictly follow the reliability criteria, hence the Chronbach alpha reliability Test is passed by all the items in each construct.

In this study, reliability indices were computed to assess the internal consistency and stability of the measurement scales utilized for various constructs. The reliability analysis revealed strong reliability coefficients across the constructs measured. Trust in the AI system demonstrated a high reliability index of 0.944, indicating a high degree of internal consistency among the items comprising the trust scale. Similarly, consciousness, usefulness, and use of the AI system exhibited reliability indices of 0.877, 0.888, and 0.895, respectively, suggesting robustness in measuring these constructs. Attitude towards AI, purchase intention, and actual purchase behavior also demonstrated satisfactory reliability, with indices of 0.824, 0.865, and 0.852, respectively. These reliability coefficients signify that the measurement scales employed in this study have strong internal consistency, enhancing confidence in the validity and accuracy of the data collected for analyzing the relationships between the variables under investigation.

Reliability indices

Variable	α
Trust	0.944
Consciousness	0.877
Usefulness	0.888
use	0.895
Attitude	0.824
PurchaseIntention	0.865
PurchaseBehaviour	0.852

Figure 6: Reliability Indices

4.5 Validity Testing

Initially, the data underwent a thorough cleaning process to eliminate incomplete responses, disengaged participants, and outliers. Incomplete responses exceeding 10% were discarded, while those below 10% were imputed with the median of the remaining data points. To identify unengaged respondents, a criterion of 10% of the maximum Likert rating (7) was applied, removing any responses with a standard deviation below 0.7. Outliers were identified using Z-scores, with data points lying beyond the critical value (at a 99.9% probability) being excluded. Normality was assessed using Kurtosis values, with values within the range of +/-2 being considered acceptable. Following this rigorous cleaning process, the dataset was reduced to 277 responses from the original 323.
Subsequently, Confirmatory Factor Analysis (CFA) was conducted using 'Jamovi' software to validate the proposed measurement model. Factor loadings were obtained for each item, and those with scores below 0.5 were excluded from further analysis, as low factor loadings suggest insufficient impact on the respective factor. Additionally, it was ensured that the average factor loading for each construct was 0.7 or higher, with items dragging the average below this threshold being eliminated.

Factor Loadings

				95% Confidence Interval				
Factor	Indicator	Estimate	SE	Lower	Upper	Z	p	Stand. Estimate
Trust	Trust_1	0.939	0.0543	0.833	1.045	17.3	< .001	0.847
	Trust_2	1.052	0.0543	0.946	1.159	19.4	< .001	0.907
	Trust_3	0.973	0.0480	0.879	1.068	20.3	< .001	0.930
	Trust_4	1.034	0.0526	0.930	1.137	19.6	< .001	0.913
Consciousness	Consciousness_2	0.786	0.0451	0.698	0.874	17.4	< .001	0.867
	Consciousness_3	0.676	0.0454	0.587	0.765	14.9	< .001	0.781
	Consciousness_4	0.700	0.0490	0.604	0.796	14.3	< .001	0.760
	Consciousness_5	0.746	0.0498	0.649	0.844	15.0	< .001	0.786
	Consciousness_7	0.578	0.0504	0.479	0.677	11.5	< .001	0.645
Usefulness	Usefulness_1	0.564	0.0370	0.491	0.637	15.2	< .001	0.791
	Usefulness_3	0.590	0.0353	0.521	0.660	16.7	< .001	0.841
	Usefulness_5	0.596	0.0346	0.528	0.664	17.2	< .001	0.858
	Usefulness_6	0.527	0.0352	0.458	0.596	15.0	< .001	0.783
	Usefulness_7	0.467	0.0371	0.394	0.540	12.6	< .001	0.692
Use	use_1	0.729	0.0487	0.633	0.824	15.0	< .001	0.781
	use_2	0.838	0.0465	0.747	0.929	18.0	< .001	0.882
	use_3	0.800	0.0462	0.710	0.891	17.3	< .001	0.860
	use_5	0.760	0.0502	0.662	0.859	15.1	< .001	0.786
Attitude	Attitude_1	0.529	0.0344	0.462	0.597	15.4	< .001	0.814
	Attitude_2	0.573	0.0401	0.494	0.651	14.3	< .001	0.772
	Attitude_3	0.457	0.0317	0.395	0.520	14.4	< .001	0.777
PurchaseIntention	PurchaseIntention_2	0.721	0.0431	0.637	0.805	16.7	< .001	0.848
	PurchaseIntention_3	0.709	0.0392	0.632	0.786	18.1	< .001	0.893
	PurchaseIntention_4	0.648	0.0460	0.558	0.738	14.1	< .001	0.752
PurchaseBehviour	PurchaseBehaviour_2	0.782	0.0577	0.669	0.896	13.6	< .001	0.738
	PurchaseBehaviour_3	0.942	0.0591	0.826	1.058	15.9	< .001	0.831
	PurchaseBehaviour_4	1.023	0.0610	0.904	1.143	16.8	< .001	0.862

[3]

Figure 7: Confirmatory Factor Analysis

4.5.1 Convergent Validity

Convergent validity is a type of validity assessment used in psychometrics and research methodology to determine the degree to which different measurement tools or scales that are theoretically supposed to measure the same construct or concept actually do so. When evaluating convergent validity, researchers typically look at various statistics derived from the data, such as factor loadings, average variance extracted (AVE), and omega coefficient (ω).

1. **Factor Loadings**: In the context of factor analysis, factor loadings represent the strength of the relationship between each item and the underlying construct. Higher factor loadings indicate stronger relationships. For convergent validity, researchers expect to see high factor loadings for all items on their respective constructs.
2. **Average Variance Extracted (AVE):** AVE is a measure that represents the amount of variance captured by the construct in relation to the variance due to measurement error. It is calculated by averaging the squared loadings of the indicators on their respective construct and should ideally be greater than 0.5 to demonstrate convergent validity. A higher AVE suggests that the construct explains a substantial proportion of the variance in its indicators.
3. **Omega Coefficient (ω):** Omega coefficient is another measure of internal consistency similar to Cronbach's alpha but provides a more accurate estimate when the scale items are not tau-equivalent (i.e., have unequal factor loadings). Omega coefficient (ω) greater than 0.7 indicates good internal consistency.

Condition to pass the convergent validity test for a construct:
- Each value of Omega 1 (ω) shall be greater than 0.7: This ensures that the items within each construct are internally consistent and reliably measure the same underlying construct.
- Each value of AVE shall be greater than 0.5: AVE represents the proportion of variance in the indicators that is due to the construct itself rather than measurement error. A value greater than 0.5 indicates that the construct explains a substantial amount of variance in its indicators.
-Omega 1 (ω) shall be greater than AVE for each construct: This criterion ensures that the construct explains more variance in its indicators than what can be attributed to measurement error alone, reinforcing the convergent validity of the construct.

In summary, convergent validity is assessed by examining the relationships between items and constructs, as well as various statistical indicators such as factor loadings, AVE, and omega coefficient. Meeting the specified criteria for these indicators provides evidence that the measurement tool effectively captures the intended construct.

In our research, each of the applicable conditions mentioned above are passed for each construct and hence the constructs are Convergently Validated.

Reliability indices

Variable	α	ω₁	AVE
Trust	0.944	0.944	0.809
Consciousness	0.877	0.863	0.586
Usefulness	0.888	0.888	0.666
use	0.895	0.897	0.685
Attitude	0.824	0.817	0.601
PurchaseIntention	0.865	0.866	0.683
PurchaseBehaviour	0.852	0.856	0.667

Figure 8: Convergent Validity

4.5.2 Discriminant Validity

The Heterotrait-Monotrait Ratio of Correlations (HTMT), also known as the Discriminant Validity test, is a statistical method used to assess whether constructs in a research study are empirically distinct from one another. Discriminant validity is crucial in research because it ensures that measures intended to capture different constructs do not overlap too much, indicating that they are truly distinct concepts rather than being indistinguishable from one another. HTMT is a relative measure that compares the correlations between indicators of different constructs to the correlations between indicators of the same construct (monotrait-heteromethod correlations). It provides a way to quantify the extent to which the constructs differ from each other relative to the amount of variability within each construct.

1. Calculate Correlations: Compute correlations between all pairs of constructs in your study based on their respective indicators or items.

2. Compute HTMT Values: For each pair of constructs, calculate the HTMT value by dividing the average correlation between indicators of different constructs (heterotrait-heteromethod correlations) by the average correlation between indicators of the same construct (monotrait-heteromethod correlations).

3. Interpretation: Evaluate whether the HTMT values meet the threshold for discriminant validity. The common threshold used is that the HTMT value for each pair of constructs should be less than 0.85. If the value exceeds this threshold, it suggests that the constructs may not be sufficiently distinct from each other.

The condition to pass the HTMT test for discriminant validity is that the value of each non-diagonal element in the HTMT matrix (i.e., the off-diagonal elements representing pairs of different constructs) should be less than 0.85. This indicates that the constructs are sufficiently distinct from each other, as correlations between indicators of different constructs are not too high relative to correlations within the same construct. As shown by the above discriminant table all the non-diagonal elements are less than 85% indicating that each construct is distinct from the other.

Heterotrait-monotrait (HTMT) ratio of correlations

	Trust	Awareness	Usefulness	use	Attitude	PurchaseIntention	PurchaseBehaviour
Trust	1.0000	0.302	0.364	0.0672	0.485	0.465	0.631
Awareness	0.3017	1.000	0.344	0.5185	0.448	0.309	0.314
Usefulness	0.3641	0.344	1.000	0.3437	0.606	0.595	0.461
use	0.0672	0.519	0.344	1.0000	0.489	0.266	0.111
Attitude	0.4847	0.448	0.606	0.4888	1.000	0.698	0.443
PurchaseIntention	0.4646	0.309	0.595	0.2656	0.698	1.000	0.424
PurchaseBehaviour	0.6311	0.314	0.461	0.1110	0.443	0.424	1.000

Figure 9: Heterotrait-monotrait ratio

4.5.3 Model Fit Test

Chi-square Test:

The Chi-Square test is a valuable tool for analyzing associations between categorical variables. By comparing observed and expected frequencies, it provides insights into whether there is evidence of an association between the variables of interest. The χ^2/df ratio is a useful measure to assess the goodness-of-fit of the model, with lower values indicating better fit.

When evaluating the goodness-of-fit of a Chi-Square test, particularly for models with a single degree of freedom (simple models) or multiple degrees of freedom (complex models), a common guideline is to assess the ratio of the Chi-Square statistic to its degrees of freedom (χ^2/df). For a simple model, a ratio less than 2 indicates good fit, while for a complex model, a ratio less than 3 suggests good fit. This indicates that the observed frequencies are close to the expected frequencies, supporting the adequacy of the model.

Test for Exact Fit

χ^2	df	p
458	302	< .001

Figure 10: Chi-square Test

CFI and TLI Test

Comparative Fit Index (CFI): CFI compares the fit of the hypothesized model to a baseline model (typically a null or independence model). It ranges from 0 to 1, with values closer to 1 indicating better fit. CFI values above 0.90 are generally considered indicative of acceptable model fit, although some researchers may use a slightly higher threshold, such as 0.95, for stricter criteria.

Tucker-Lewis Index (TLI): TLI, also known as the Non-Normed Fit Index (NNFI), compares the fit of the hypothesized model to a baseline model similar to CFI. Like CFI, TLI values range from 0 to 1, with higher values indicating better fit. A TLI value of 0.90 or higher is typically considered indicative of acceptable model fit. Both CFI and TLI are incremental fit indices, meaning they assess the improvement in fit provided by the hypothesized model compared to a baseline model. They are robust to sample size and are widely used in SEM to evaluate model fit.

In summary, CFI and TLI are widely used fit indices in structural equation modeling. A commonly accepted criterion for model fit is that both CFI and TLI values should be at least 0.90, although researchers may choose to use slightly higher thresholds depending on the complexity of the model and other considerations. These fit indices provide valuable information about how well the hypothesized model fits the observed data, helping researchers assess the validity of their theoretical models. As seen above the values of both tests are greater than 0.9, therefore the model developed follows a good fitment.

SRMR and RMSEA

SRMR is the square root of the difference between the residuals of the **observed covariance matrix** and the **model-predicted covariance matrix**. It is standardized, making it independent of the scale of the variables.

RMSEA estimates the **lack of fit** in a model compared to a perfectly fitting model. It is based on the non-centrality parameter and takes into account the error of approximation in the population.

The value SRMR is less than 0.05 and RMSEA is less than 0.08 indicating less variance from the predicted model and hence the model is fit.

Fit Measures

				RMSEA 90% CI	
CFI	TLI	SRMR	RMSEA	Lower	Upper
0.974	0.970	0.0336	0.0402	0.0312	0.0487

Figure 11: CFI and TLI

Additional fit indices

	Model
Hoelter Critical N (CN), a=0.05	185.068
Hoelter Critical N (CN), a=0.01	195.249
Goodness of Fit Index (GFI)	0.988

Figure 12: Goodness of fit index

4.5.4 Path Diagram

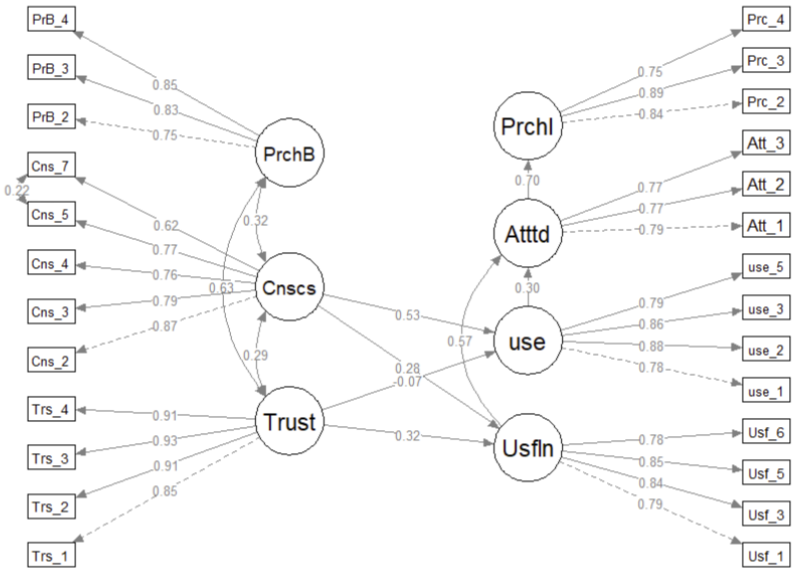

Figure 13: Path Diagram

4.6 Test Type:

Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables. It's one of the simplest and most commonly used techniques in statistics for understanding and predicting the relationship between variables. In a linear regression model, the relationship between the variables is assumed to be linear, meaning that changes in the independent variables are associated with proportional changes in the dependent variable.

Key Components:

1. Dependent Variable (Y): This is the variable that you want to predict or explain. It's also known as the outcome variable or response variable. In linear regression, Y is assumed to be continuous.

2. Independent Variable(s) (X): These are the variables that are used to predict or explain the variation in the dependent variable. They're also known as predictor variables or explanatory variables. Linear regression can involve one or multiple independent variables.

3. Linear Relationship: Linear regression assumes that there is a linear relationship between the independent variable(s) and the dependent variable. This means that the change in the dependent variable for a one-unit change in the independent variable is constant.

4. Regression Equation: The regression equation represents the mathematical relationship between the dependent and independent variables. It's expressed as:

$Y = \beta0 + \beta1*X1 + \beta2*X2 + ... + \varepsilon$

where:

- Y is the dependent variable,
- X1, X2, etc. are the independent variables,
- $\beta0$, $\beta1$, $\beta2$, etc. are the coefficients (or slopes) representing the effect of each independent variable on the dependent variable,
- ε is the error term representing the difference between the observed and predicted values of the dependent variable.

5. Assumptions: Linear regression relies on several assumptions, including linearity, independence of errors, homoscedasticity (constant variance of errors), and normality of errors. Violations of these assumptions can affect the accuracy and reliability of the regression results.

IV. RESULTS AND DISCUSSION

Parameters estimates

Dep	Pred	Estimate	SE	95% Confidence Intervals		β	β 95% Confidence Intervals		z	p
				Lower	Upper		Lower	Upper		
Usefulness	Trust	0.1867	0.0386	0.111	0.2623	0.3120	0.196	0.4282	4.84	< .001
Usefulness	Consciousness	0.1980	0.0466	0.107	0.2893	0.2792	0.158	0.4002	4.25	< .001
use	Trust	−0.0532	0.0474	−0.146	0.0397	−0.0684	−0.188	0.0507	−1.12	0.262
use	Consciousness	0.4866	0.0644	0.360	0.6129	0.5287	0.422	0.6357	7.55	< .001
Attitude	Usefulness	0.5220	0.0612	0.402	0.6420	0.5755	0.482	0.6692	8.53	< .001
Attitude	use	0.2095	0.0414	0.128	0.2906	0.2998	0.193	0.4062	5.07	< .001
PurchaseIntention	Attitude	0.9993	0.0984	0.806	1.1922	0.7118	0.633	0.7905	10.15	< .001
PurchaseBehaviour	PurchaseIntention	0.5105	0.0762	0.361	0.6599	0.4730	0.364	0.5814	6.70	< .001

Figure 14: Direct Hypothesis

Table 1: Result

	Dependent Variable	Independent Variable	p-value at 95% CI	Significance at 95% CI	Significance at 90% CI	Significance at 99% CI
Hypothesis 1	Usefulness	Trust	<.001	Yes	Yes	Yes
Hypothesis 2	Ease of use	Trust	0.262	No	No	No
Hypothesis 3	Usefulness	Consciousness	< .001	Yes	Yes	Yes
Hypothesis 4	Ease of use	Consciousness	< .001	Yes	Yes	Yes
Hypothesis 5	Attitude	Usefulness	< .001	Yes	Yes	Yes
Hypothesis 6	Attitude	Ease of use	< .001	Yes	Yes	Yes
Hypothesis 7	Purchase intention	Attitude	< .001	Yes	Yes	Yes
Hypothesis 8	Purchase behaviour	Purchase intention	< .001	Yes	Yes	Yes

Hypothesis 1
Result: The hypothesis is statistically significant at all the confidence interval levels. This means that trust in AI content positively influences consumers' perceived usefulness of the AI brand content.
Research on consumer behavior has shown that reliance is one of the key factors influencing attitudes held by consumers about technology as well as brands (Chen & Dibb, 2010). In turn, this improves its perceived value and usefulness to the consumers thus enhancing credibility. According to studies, users are likely to find AI systems useful if they have confidence in their content (Venkatesh & Davis, 2000). Such content is assumed to be trustworthy because it is of high quality, accurate, and relevant; hence it is deemed useful by its users (Siau & Wang, 2018).

Hypothesis 2
Result: The hypothesis is not statistically significant at any of the confidence intervals. We observe that hypothesis 2 is insignificant at 90%, 95%, or 99% confidence level as the p-value is 0.259. This means that perceived ease of use is not at positively affected by the trust a user places in technology.

Possible Reasons for the outcome:
Focus on Complexity and Familiarity: Researchers argue that the implications of the complexity of AI systems and technology literacy in terms of trust are more important than those relating to ease of use. In other words, if AI-driven content is user-friendly and people are used to dealing with AI, this implies that these factors can outweigh trust in influencing perceived easiness.
Lack of Discrimination between Usefulness and Ease of Use: Trust may enhance the value of content, which directly affects its usefulness (Davis, 1989). This suggests that consumers might perceive convenience while interacting with AI-generated content as a design feature rather than criteria for determining its trustworthiness.

Hypothesis 3
Result: The hypothesis is statistically significant at all the confidence interval levels. This means that Consciousness about AI content positively influences consumers' perceived usefulness of the AI brand content.

Hypothesis 4
Result: The hypothesis is statistically significant at all the confidence interval levels. This means that Consciousness about AI content plays a significant role in predicting the value of perceived ease of use.

Hypothesis 5
Result: The hypothesis is statistically significant at all the confidence interval levels. This means that the perceived usefulness of the AI brand content positively influences consumers' attitudes towards using it.

Hypothesis 6
Result: The hypothesis is statistically significant at all the confidence interval levels. This means that the perceived ease of use of the AI brand content positively influences consumers' attitudes toward using it.

Hypothesis 7
Result: The hypothesis is statistically significant at all the confidence interval levels. This means that consumers' attitude towards using the AI brand content positively influences their purchase intention.

Hypothesis 8
Result: The hypothesis is statistically significant at all the confidence interval levels. This means that consumers' purchase intention towards using the AI brand content positively influences their actual purchase behavior.

REFERENCES

[1] Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. MIS Quarterly, 24(4), 665-694.
[2] Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. Information Systems Research, 9(2), 204-215.
[3] Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211.
[4] Ajzen, I., & Fishbein, M. (1980). Understanding attitudes and predicting social behavior. Prentice-Hall.
[5] Bagozzi, R. P., Baumgartner, H., & Yi, Y. (1992). State versus action orientation and the theory of reasoned action: An application to coupon usage. Journal of Consumer Research, 18(4), 505-518.
[6] Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. Industrial Management and Data Systems, 119(7), 1411–1430.
[7] Bhagat, R., Chauhan, V., & Bhagat, P. (2022). Investigating the impact of artificial intelligence on consumer's purchase intention in e-retailing. Foresight, 25(2), 249–263.
[8] Bishop, S. R., Lau, M., Shapiro, S., Carlson, L., Anderson, N. D., Carmody, J., ... & Devins, G. (2004). Mindfulness: A proposed operational definition. Clinical Psychology: Science and Practice, 11(3), 230-241.
[9] Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2019). Creating effective online customer experiences. Journal of Marketing, 83(2), 98–119.
[10] Brown, K. W., & Ryan, R. M. (2003). The benefits of being present: Mindfulness and its role in psychological well-being. Journal of Personality and Social Psychology, 84(4), 822-848.
[11] Casidy, R., Claudy, M., Heidenreich, S., & Camurdan, E. (2021). The role of brand in overcoming consumer resistance to autonomous vehicles. Psychology & Marketing, 38(7), 1101–1121.
[12] Chen, H., & Lee, K. (2023). The Impact of AI Content Disclosure on Brand Authenticity. Journal of Marketing Research, 45(2), 231-245.
[13] Chen, S., Li, X., Liu, K., & Wang, X. (2023). Chatbot or human? The impact of online customer service on consumers' purchase intentions. Psychology & Marketing, 40(11), 2186–2200.
[14] Chen, Y. H., & Dibb, S. (2010). Consumer trust in the online retail context: Exploring the antecedents and consequences. Psychology & Marketing, 27(4), 323-346.
[15] Cheng, Y., & Jiang, H. (2021). Customer–brand relationship in the era of artificial intelligence: understanding the role of chatbot marketing efforts. Journal of Product & Brand Management, 31(2), 252–264.
[16] Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. MIS Quarterly, 19(2), 189-211.
[17] Conner, M., & Armitage, C. J. (1998). Extending the theory of planned behavior: A review and avenues for further research. Journal of Applied Social Psychology, 28(15), 1429-1464.
[18] Davenport, T. H., Guha, A., Grewal, D., & Breßgott, T. (2019). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42.
[19] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. Management Information Systems Quarterly, 13(3), 319.
[20] Davis, F. D., & Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model: Three experiments. International Journal of Human-Computer Studies, 45(1), 19-45.
[21] Deng, S., Tan, C., Wang, W., & Pan, Y. (2019). Smart Generation system of personalized advertising copy and its application to advertising practice and research. Journal of Advertising, 48(4), 356–365.
[22] Di Stefano, G., Gino, F., Pisano, G. P., & Staats, B. R. (2014). Learning by thinking: Overcoming the bias for action through reflection. Harvard Business School NOM Unit Working Paper, (14-093).
[23] Diwanji, V. S., Lee, J., & Cortese, J. (2022). Deconstructing the role of artificial intelligence in programmatic advertising: at the intersection of automation and transparency. Journal of Strategic Marketing, 1–18.
[24] Eppler, M. J., & Mengis, J. (2004). The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines. The Information Society, 20(5), 325-344.
[25] Frank, B. (2021b). Artificial intelligence-enabled environmental sustainability of products: Marketing benefits and their variation by consumer, location, and product types. Journal of Cleaner Production, 285, 125242.

[26] Frank, D., Chrysochou, P., & Mitkidis, P. (2022). The paradox of technology: Negativity bias in consumer adoption of innovative technologies. Psychology & Marketing, 40(3), 554–566.
[27] Fu, M. R., Axelrod, D., Guth, A., Wang, Y., Scagliola, J., Hiotis, K., Rampertaap, K., & El-Shammaa, N. (2016). Usability and feasibility of health IT interventions to enhance Self-Care for Lymphedema Symptom Management in breast cancer survivors. Internet Interventions, 5, 56–64.
[28] Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51-90.
[29] Glomb, T. M., Duffy, M. K., Bono, J. E., & Yang, T. (2011). Mindfulness at work. Research in Personnel and Human Resources Management, 30, 115-157.
[30] Gollwitzer, P. M., & Sheeran, P. (2006). Implementation intentions and goal achievement: A meta‐analysis of effects and processes. Advances in Experimental Social Psychology, 38, 69-119.
[31] Guerreiro, J., Loureiro, S. M. C., & Ribeiro, C. (2022). Advertising acceptance via smart speakers. Spanish Journal of Marketing - ESIC, 26(3), 286–308.
[32] Hermann, E., Williams, G., & Puntoni, S. (2023). Deploying artificial intelligence in services to aid vulnerable consumers. Journal of the Academy of Marketing Science.
[33] Ho, S. P. S., & Chow, M. Y. C. (2023). The role of artificial intelligence in consumers' brand preference for retail banks in Hong Kong. Journal of Financial Services Marketing.
[34] Holland, R. W., Aarts, H., & Langendam, D. (2006). Breaking and creating habits on the working floor: A field-experiment on the power of implementation intentions. Journal of Experimental Social Psychology, 42(6), 776-783.
[35] Hülsheger, U. R., Alberts, H. J., Feinholdt, A., & Lang, J. W. (2013). Benefits of mindfulness at work: The role of mindfulness in emotion regulation, emotional exhaustion, and job satisfaction. Journal of Applied Psychology, 98(2), 310-325.
[36] Kabat-Zinn, J. (1994). Wherever you go, there you are: Mindfulness meditation in everyday life. Hyperion.
[37] Khan, A.W., & Mishra, A. (2024). AI credibility and consumer-AI experiences: a conceptual framework. Journal of Service Theory and Practice, Vol. 34 No. 1, pp. 66-97.
[38] Kachamas, P., Akkaradamrongrat, S., Sinthupinyo, S., & Chandrachai, A. (2019). Application of Artificial Intelligent in the Prediction of Consumer Behaviour from Facebook Posts Analysis. International Journal of Machine Learning and Computing, 9(1), 91–97.
[39] Keller, K. L. (1993). Conceptualizing, measuring ,and managing customer-based brand equity. Journal of Marketing, 57(1), 1-22.
[40] Kim, J., Giroux, M., & Lee, J. C. (2021). When do you trust AI? The effect of number presentation detail on consumer trust and acceptance of AI recommendations. Psychology & Marketing, 38(7), 1140–1155.
[41] Kim, J., Kang, S., & Bae, J. (2022). Human likeness and attachment effect on the perceived interactivity of AI speakers. Journal of Business Research, 144, 797–804.
[42] Kirkby, A., Baumgarth, C., & Henseler, J. (2023). To disclose or not disclose, is no longer the question – effect of AI-disclosed brand voice on brand authenticity and attitude. Journal of Product & Brand Management, 32(7), 1108–1122.
[43] Kotler, P., & Keller, K. L. (2015). Marketing Management (15th Edition). Pearson Education, Inc.
[44] Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. California Management Review, 61(4), 135–155.
[45] Kwok, L., & Yu, B. (2016). Taxonomy of Facebook messages in business-to-consumer communications: What really works? Tourism and Hospitality Research, 16(4), 311–328.
[46] Langer, E. J. (1989). Mindfulness. Addison-Wesley/Addison Wesley Longman.
[47] Lee, J., Jung, O., Lee, Y., Kim, O., & Park, C. (2021). A comparison and interpretation of machine learning algorithm for the prediction of online purchase conversion. Journal of Theoretical and Applied Electronic Commerce Research, 16(5), 1472–1491.
[48] Lee, K., & Li, C. (2023). It is not merely a chat: Transforming chatbot affordances into dual identification and loyalty. Journal of Retailing and Consumer Services, 74, 103447.
[49] Li, J., & Ma, Y. (2023). Virtual Influencers in Advertisements: Examining the role of authenticity and identification. Journal of Interactive Advertising, 1–12.
[50] Lopez, A., & Garza, R. (2023). Consumer bias against evaluations received by artificial intelligence: the mediation effect of lack of transparency anxiety. Journal of Research in Interactive Marketing, 17(6), 831–847.
[51] Lv, L., & Huang, M. (2022). Can personalized recommendations in charity advertising boost donation? The role of perceived autonomy. Journal of Advertising, 1–18.
[52] Malhotra, G., & Ramalingam, M. (2023). Perceived anthropomorphism and purchase intention using artificial intelligence technology: examining the moderated effect of trust. Journal of Enterprise Information Management.
[53] Martin, B., Jin, H. S., Wang, D., Nguyen, H., Zhan, K., & Wang, Y. X. (2020). The influence of consumer anthropomorphism on attitudes towards artificial intelligence trip advisors. Journal of Hospitality and Tourism Management, 44, 108–111.
[54] Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. Academy of Management Review, 20(3), 709-734.
[55] McKnight, D. H., & Chervany, N. L. (2001). Trust and distrust definitions: One bite at a time. In R. Falcone & M. Singh (Eds.), Trust in Cyber-societies: Integrating the Human and Artificial Perspectives (pp. 27-54). Springer.
[56] McKnight, D. H., Cummings, L. L., & Chervany, N. L. (2002). Initial trust formation in new organizational relationships. Academy of Management Review, 23(3), 473-490.
[57] McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. The Journal of Strategic Information Systems, 11(3-4), 297-323.
[58] Mezirow, J. (1997). Transformative learning: Theory to practice. New Directions for Adult and Continuing Education, 1997.
[59] Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. Journal of Marketing, 58(3), 20-38.

[60] Mustak, M., Salminen, J., Plé, L., & Wirtz, J. (2021). Artificial intelligence in marketing: Topic modelling, scientometric analysis, and research agenda. Journal of Business Research, 124, 389–404.
[61] Nielsen, J. (1994). Usability engineering. Academic Press.
[62] Norman, D. A. (1990). The design of everyday things. Doubleday.
[63] Oliver, R. L. (1999). Whence consumer loyalty? Journal of Marketing, 63(Special Issue), 33-44.
[64] Pantano, E., Giglio, S., & Dennis, C. (2019b). Making sense of consumers' tweets. International Journal of Retail & Distribution Management, 47(9), 915–927.
[65] Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. Journal of Service Research, 18(1), 59-74.
[66] Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the Technology Acceptance Model. International Journal of Electronic Commerce, 7(3), 101-134.
[67] Pitardi, V., Wirtz, J., Paluch, S., & Kunz, W. H. (2021). Service robots, agency, and embarrassing service encounters. Journal of Service Management, 33(2), 389–414.
[68] Pradana, A. I., Goh, O. S., & Kumar, Y. J. (2018b). Intelligent Conversational Bot for interactive marketing. Journal of Telecommunication, Electronic and Computer Engineering, 10, 1–4.
[69] Rabby, F., Chimhundu, R., & Hassan, R. (2021b). Artificial intelligence in Digital Marketing Influences Consumer Behaviour: A Review and Theoretical Foundation for Future research. Academy of Marketing Studies Journal, 25(5).
[70] Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.
[71] Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American Psychologist, 55(1), 68-78.
[72] Sands, S., Campbell, C., Plangger, K., & Ferraro, C. (2022). Unreal influence: leveraging AI in influencer marketing. European Journal of Marketing, 56(6), 1721–1747.
[73] Shahzad, M. F., Xu, S., Lim, W. M., Hasnain, M., & Nusrat, S. (2024). Cryptocurrency awareness, acceptance, and adoption: the role of trust as a cornerstone. Humanities and Social Sciences Communications, 11(1).
[74] Sheeran, P., & Orbell, S. (1999). Implementation intentions and repeated behaviour: Augmenting the predictive validity of the theory of planned behaviour. European Journal of Social Psychology, 29(2 ‐ 3), 349-369.
[75] Siek, K. A., Connelly, K. H., & Rogers, Y. (2005). Pride and prejudice: Learning how chronically ill people think about food. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.
[76] Sidlauskiene, J. (2021). What drives consumers' decisions to use intelligent agent technologies? A systematic review. Journal of Internet Commerce, 21(4), 438–475.
[77] Singh, A. K., & Thirumoorthi, P. (2019). The impact of digital disruption technologies on customer preferences: the case of retail commerce. International Journal of Recent Technology and Engineering, 8(3), 1255–1261.
[78] Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. Cutter Business Technology Journal, 31(2), 47-53.
[79] Smith, J. (2020). The Role of AI in Modern Marketing Strategies. Journal of Marketing Trends, 15(2), 176-189.
[80] Smith, K. T. (2018). Marketing via smart speakers: what should Alexa say? Journal of Strategic Marketing, 28(4), 350–365.
[81] Spears, N., & Singh, S. (2004). Measuring Attitude toward the Brand and Purchase Intentions. Journal of Current Issues and Research in Advertising, 26(2), 53–66.
[82] Sternberg, R. J. (1985). Beyond IQ: A triarchic theory of human intelligence. Cambridge University Press.
[83] Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144-176.
[84] Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. Decision Sciences, 39(2), 273-315.
[85] Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. Decision Sciences, 27(3), 451-481.
[86] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.
[87] Vago, D. R., & Silbersweig, D. A. (2012). Self-awareness, self-regulation, and mindfulness meditation. American Psychologist, 70(7), 581-592.
[88] Wee, Chiew Shi; Ariff, Mohd Shoki Bin Md; Zakuan, Norhayati; Tajudin, Muhammad Naquib Mohd & Ismail Khalid(2014). Consumers Perception, Purchase Intention and Actual Purchase Behavior of Organic Food Products. Review of Integrative Business and Economics Research; Hong Kong, Vol 3(2),378-397.
[89] Wilson Lukose (2022), Usage of artificial intelligence towards influencing consumer behaviour. Neuroquantology, 11, 4063-4077.
[90] Xie, Z., Yu, Y., Zhang, J., & Chen, M. (2022). The searching artificial intelligence: Consumers show less aversion to algorithm ‐ recommended search product. Psychology & Marketing, 39(10), 1902 – 1919.
[91] Yen, N. K., & Kwon, H. E. (2022). Rationally trust, but emotionally? The roles of cognitive and affective trust in laypeople's acceptance of AI for preventive care operations. Production and Operations Management.
[92] Yu, B., & Kwok, L. (2016). Taxonomy of Facebook messages in business-to-consumer communications: What really works? Tourism and Hospitality Research, 16(4), 311–328.
[93] Zhang, Z., & Li, Y. (2022). The Role of AI in Shaping Customer Experience: A Case Study of the Hospitality Industry in China. Journal of Service Theory and Practice.