

Modeling Consumer Responses to AI-Generated Food Images: The Role of Visual Authenticity, Perceived Risk, and Trust

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Abstract: *The growing adoption of generative artificial intelligence (AI) in digital food marketing raises important questions regarding its impact on consumer behavior. This study aims to examine how AI-generated food images influence purchase intention by integrating perceived visual authenticity, perceived risk, and trust within the Stimulus–Organism–Response (S-O-R) framework. A quantitative explanatory approach was employed, using a cross-sectional survey of 204 Indonesian consumers who had purchased food online within the past six months. Data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS). The findings reveal that AI-generated images significantly enhance both trust and purchase intention. Perceived visual authenticity emerges as the strongest predictor of trust and directly increases purchase intention, highlighting the importance of realistic, credible visual representations. In contrast, perceived risk does not directly affect purchase intention but negatively influences trust, indicating that its impact operates indirectly. Furthermore, trust plays a significant mediating role in the relationships between AI-generated images and purchase intention, as well as between perceived risk and purchase intention. However, trust does not mediate the relationship between perceived visual authenticity and purchase intention. This study concludes that consumer responses in AI-driven marketing contexts are primarily shaped by visual perception and trust rather than perceived risk. In practice, the findings suggest that businesses should prioritize authentic, transparent AI-generated visuals to strengthen consumer trust and enhance purchase intention.*

Keywords: *AI-generated images, Food Marketing², Visual Authenticity³, Perceived Risk, Trust*

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1. INTRODUCTION

1.1 Background

Generative Artificial Intelligence (GAI) is revolutionizing digital marketing by auto-content creation [1]. Advances in artificial intelligence, particularly generative AI, have significantly transformed digital marketing practices [2]. In the food industry, businesses can now produce highly realistic product images without live photography, this technology offers significant cost-efficiency and flexibility in visual content production [3]. However, the use of AI-generated images raises new issues on the one hand, this label reflects transparency [1]. On the other hand, the fact that AI generated the image can influence how consumers assess the product's visual authenticity, increasing risk perceptions and undermining brand trust [4].

In the context of food marketing, visuals play a crucial role because consumers cannot touch, smell, or taste the product before purchasing [3]. Therefore, any changes in visual perception can directly impact purchase intention [5]. The primary research question is how AI labeling of food images

influences consumer responses, specifically through perceived visual authenticity, perceived risk, and trust. This technological advancement raises significant ethical concerns regarding the transparency of visual information [2]. AI generated image emerged in response to regulatory and business ethics demands to provide consumers with clarity regarding the origins of the visual content they consume [1]. The main issue at the heart of this research is the psychological ambiguity in consumers' minds; whether the labeling is perceived as a form of radical honesty from a brand, or instead triggers doubts that damage the credibility of the food products displayed.

The link between AI usage and Perceived Visual Authenticity is a critical factor in modern consumer behavior [6]. In the context of culinary marketing, visual authenticity is not simply a technical matter of lighting or composition, but rather a signal of quality and sensory promise [7]. When a food image is labeled "AI-Generated," consumers tend to critically evaluate how well it reflects the product's physical reality [1]. If the visual is perceived as too perfect or "too good to be true," it can erode perceptions of authenticity [4]. This decline in authenticity will linearly increase Perceived Risk, where consumers begin to worry about a significant discrepancy between the expectations established by the AI algorithm and the experience of receiving the product (the expectation vs. reality phenomenon) [8]. The urgency of this research within the scope of digital marketing management lies in the role of Trust (Z1) as a key mediator connecting visual perception with economic action [9]. In the digital economy, trust is no longer merely an add-on; it is the primary currency that determines the success of transactions [10]. Without solid trust, even the most accurate information will be unable to drive purchase intention [11]. Failure to manage Trust when using generative AI technology can lead to a loss of consumer loyalty and long-term damage to brand reputation [8].

This research is motivated by the urgent need to understand the paradigm shift in consumer behavior toward artificial content. Theoretically, there is a gap in the management literature regarding how the interaction between AI transparency and perceived risk influences overall purchase intention. Practically, this research aims to address the dilemma facing marketing managers: whether the use of flawless yet "honest" AI visuals will increase or decrease Purchase Intention (Y1). By systematically modeling consumer responses, this research is expected to provide a strategic framework for the food industry to adopt AI technology without compromising brand integrity or long-term customer relationships.

1.2 Scope and Limitation

The presence of artificial intelligence-based visual content in digital marketing creates new cognitive dynamics that require in-depth empirical exploration [12]. As transparency standards through content labeling increase, crucial questions arise about how these information mechanisms influence consumer psychology. Conceptually, this study focuses on the psychological dynamics arising from the presence of AI generated image(X1). The scope of the variables includes consumer assessments of Perceived Visual Authenticity (X2) and Perceived Risk (X3) as antecedents of Trust (Z1), which ultimately determines Purchase Intention (Y1). Demographically, this study targets active consumer groups on digital platforms (such as social media and food delivery apps) with fairly good technological literacy, especially the millennial and Gen Z generations. Geographically, this study was conducted in the Indonesian digital market to capture the phenomenon of technological adaptation in developing economies.

This study has several limitations that need to be considered for proper interpretation of the results. First, Substantive Limitation: This study evaluated consumer responses only to visual cues (images) and AI label information, not to the physical quality of food products. Second, Methodological Limitation: Data collection was conducted through an experimental scenario-based survey, which, while effective for measuring perceptions, may have limitations in capturing real-world impulse buying behavior. Third, Contextual Limitation: The results of this study may have lower

generalizability when applied to industries outside the food category, given the unique characteristics of consumers' emotional and sensory engagement with food products.

2. LITERATURE REVIEW

2.1 Theory

This research adopts the Stimulus–Organism–Response (S-O-R) approach as a theoretical foundation for analyzing the complexity of consumer behavior in the context of AI-generated images in digital marketing. [13]. In this model, AI generated image (X1) is positioned as an external stimulus in the form of an informational cue that provides transparency regarding the technological origins of a product image [14]. The presence of this label does not stand alone, but interacts with other visual attributes such as Perceived Visual Authenticity (X2) which represents the aesthetics of the image, and Perceived Risk (X3), which arises as a consequence of technological uncertainty [4].

The internal process or psychological state of consumers within the S-O-R framework is referred to as an organism, represented in this study by Trust (Z1) [15]. When consumers see an AI label on a food image, they conduct cognitive and affective evaluations: whether the use of AI enhances brand honesty (authenticity) or triggers concerns about product quality manipulation (risk) [15]. If the AI label is perceived as a form of ethical responsibility and the image remains authentic and poses no threats, trust will be strengthened [16]. Conversely, if the AI label actually increases risk perception, the foundation of trust in digital transactions will be weakened [17].

The final stage of this model is response, which is the actual behavior or intention resulting from the internal process, as reflected in Purchase Intention (Y1) [18]. The S-O-R framework is highly relevant to explaining the title of this study because it illustrates how additional information about the use of AI in food images does not immediately trigger a purchase but must first pass through the "black box" of consumer evaluation [19]. By positioning Trust as a mediator, this model systematically maps how visual honesty and risk mitigation are key prerequisites for AI labeling to be positively received by food consumers, ultimately leading to a purchase decision [9].

2.2 Conceptual Framework

The conceptual model in this study explains the psychological mechanisms underlying consumers' reactions to AI-generated images of food products. The model integrates technical transparency, visual authenticity, and perceived risk to examine their impact on purchase intention. External stimuli are first processed through consumers' internal evaluations before producing a behavioral response.

The independent variables consist of AI generated image(X1), Perceived Visual Authenticity (X2), and Perceived Risk (X3), which simultaneously influence Trust (Z1). Transparency through AI-generated images and authentic visual representations is expected to strengthen trust in the digital context, while perceived risk may weaken it due to uncertainty about product quality. The model also posits that visual authenticity (X2) influences perceived risk (X3). Trust (Z1) functions as a central mediating variable linking initial perceptions to Purchase Intention (Y1). This indicates that AI-labeled food images do not directly generate purchase intention; rather, trust must first be established. Once trust is formed through positive evaluations of labeling, authenticity, and reduced risk, psychological barriers decrease, ultimately increasing consumers' intention to purchase.

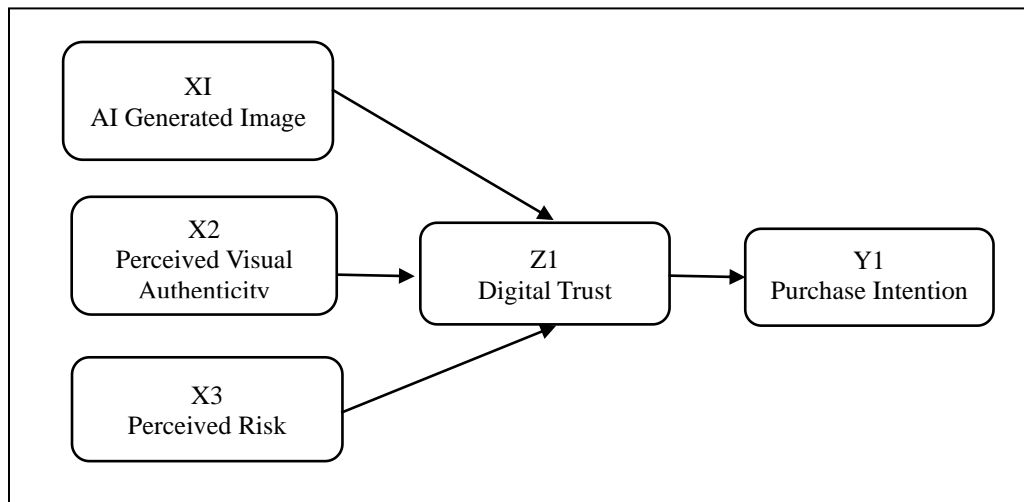


Figure 1: conceptual framework

2.3 Hypothesis

Based on the literature review and the conceptual framework developed, this study proposes a series of hypotheses to test the relationship between variables empirically:

2.2.1 The Effect of AI generated image and Visual Authenticity on Trust

Information transparency through AI generated image(X1) is predicted to convey a positive signal regarding a company's integrity, consumers tend to trust brands that are honest about their technology use (Wang et al., 2025). Similarly, Perceived Visual Authenticity (X2) determines whether the visual is perceived as an honest representation or an aesthetic misrepresentation (Bui et al., 2024). Maintaining the authenticity of visuals, even if generated by AI, will validate consumer expectations (Ziakis & Vlachopoulou, 2023).

H1: AI generated image has a positive effect on Trust.

2.2.2 The Effect of Perceived Visual Authenticity on Trust

Perceived Visual Authenticity refers to the extent to which consumers perceive that product images accurately reflect real conditions [20]. In digital food marketing, visual authenticity is crucial because consumers cannot verify the product directly before purchasing [4]. Visuals perceived as authentic tend to increase consumer confidence that the brand is conveying accurate information [21]. Based on trust theory, perceived authenticity is the basis for building trust because it reduces doubts about the brand's credibility [22]. Therefore, the higher the perceived visual authenticity, the greater the consumer's trust [23].

H2: Perceived Visual Authenticity (X2) has a positive and significant effect on Trust (Z1).

2.2.3 The Role of Perceived Risk on Trust

Perceived Risk (X3) often stems from uncertainty about the product's physical quality [24]. AI labeling can trigger concerns that the authentic product will not be as beautiful as the image [19]. The higher consumers' perceived risk of product failure, the more difficult it is for companies to build a foundation of trust [25].

H3: Perceived Risk has a positive effect Trust.

2.2.4 The Influence of Trust on Purchase Intention

Trust is consumer confidence in a brand's reliability, credibility, and integrity in an online environment [26]. In digital transactions, trust is a key factor because consumers do not

have direct access to the physical product. Various studies in digital marketing show that trust plays a key role in purchase intention [27]. When consumers have high trust in a brand, they tend to have stronger purchase intentions [5]. Therefore, the higher the trust, the more likely consumers are to make a purchase [28].

H4: Trust (Z1) has a positive and significant effect on Purchase Intention (Y1).

2.2.5 The Mediating Role of Trust

In addition to its direct influence on purchase intention, trust also acts as a mediating mechanism in the relationship between the independent variables and purchase intention [4]. In this research model, AI Generated Images, Perceived Visual Authenticity, and Perceived Risk influence purchase intention by shaping trust.

Transparency in AI generated images can increase purchase intention if consumers first build trust in the brand [19]. Similarly, the perception of authentic visuals will increase purchase intention through increased trust [29]. Conversely, high perceived risk can decrease purchase intention by weakening trust in the brand [30]. Thus, trust functions as a psychological bridge between consumers' cognitive evaluations and behavioral responses [31].

H5: Trust mediates the effect of AI generated image on Purchase Intention.

H6: Trust mediates the effect of Perceived Visual Authenticity on Purchase Intention.

H7: Trust mediates the effect of Perceived Risk on Purchase Intention.

3. METHOD

3.1 Type of Research

This research is a quantitative study with an explanatory approach that aims to test the causal relationships and influences between hypothesized variables [32]. The research design was a cross-sectional survey, in which data were collected at a specific point in time to explain consumer responses to the use of AI labels on food product images [33]. This approach was chosen to validate a theoretical model that integrates technical (AI Labeling), aesthetic (Authenticity), and psychological (Risk & Trust) aspects [34].

This study takes one culinary MSME, DeepCrunch.indo, as the research object. DeepCrunch.indo operates in the fast-food sector, specializing in crispy chicken products, and actively utilizes Instagram as its primary digital marketing channel. The MSME was selected because it has implemented AI-generated images as part of its marketing kit, particularly in producing product visuals for social media promotion. The adoption of artificial intelligence (AI) technology in generating food imagery provides a relevant empirical context, as visual presentation plays a central role in digital culinary marketing strategies.

A critical issue arises when consumers are informed that the displayed product image is not an original photograph but an AI-generated representation [35]. This condition can trigger dual consumer responses: it may enhance perceptions of innovation and transparency, or, conversely, increase skepticism and perceived risk [36]. Therefore, DeepCrunch.indo provides an appropriate case for examining the psychological mechanisms underlying consumer responses to AI-generated food images.

3.2 Population and Sample

The study population consisted of urban consumers aged 18 to 45 who had purchased food online within the past six months. This criterion was established to ensure that respondents were (1) familiar with the research context, specifically exposure to food product images on digital platforms, (2) possessed sufficient cognitive capacity and experience to evaluate visual authenticity and AI labels, and (3) were able to provide valid responses regarding perceived risk, trust, and purchase

intention. Empirical studies indicate that urban consumers have high exposure to online food ordering services and visual marketing content, making this population suitable for generalizing the findings [37].

Purposive sampling, a non-probability sampling technique, was employed to select respondents based on predetermined inclusion criteria [32]. This approach is appropriate for research requiring participants with specific experiences, such as recent online food purchases, thereby ensuring that the collected data are relevant to the study's conceptual constructs of digital trust, perceived risk, and visual authenticity.

The study targeted a minimum sample size of 200 respondents. This decision aligns with practical guidelines in partial least squares structural equation modeling (PLS-SEM), which recommend the ten-fold rule and emphasize the need for adequate statistical power. Literature suggests that PLS-SEM requires a sufficient sample size for stable parameter estimation [34]. The population in this study comprises digital-generation consumers in Indonesia (specifically in urban areas such as Yogyakarta) who actively use social media and regularly purchase food online. In accordance with SEM-PLS analysis requirements, the sample size was set at least 10 times the number of paths in the model, or a target of 150-200 respondents, to ensure the stability of the model estimates [38].

3.3 Research Instrument

The primary data collection instrument is an electronic questionnaire distributed via an online platform. The questionnaire uses a 7-point Likert scale ranging from 1 = Strongly Disagree to 7 = Strongly Agree to measure AI-generated images, Perceived Visual Authenticity, Perceived Risk, Trust, and Purchase Intention. The use of a 7-point scale is supported in behavioral research because it provides greater response variability, improves measurement sensitivity, and enhances reliability compared to shorter scales [39]. Empirical studies show that seven response categories optimize psychometric properties while maintaining respondent comfort and discrimination accuracy. Additionally, increased variance benefits SEM-based analysis by supporting more stable parameter estimation [34].

3.4 Data Collection Technique

Data collection is conducted through a self-administered online survey, a method widely used in behavioral and marketing research to efficiently gather primary data from targeted respondents [32]. The stimulus material used in this study consists of food product images from DeepCrunch.indo. Respondents are first exposed to these AI-generated product visuals to simulate real digital marketing conditions. After viewing the stimulus, respondents are asked to evaluate the statements based on their perceptions and feelings toward the AI-generated images.

Data collection is conducted through a self-administered online survey, a method widely used in behavioral and marketing research to efficiently gather primary data from targeted respondents (Creswell & Creswell, 2018). Respondents will be provided with a questionnaire link that begins with a stimulus displaying AI-generated images of food products. After viewing the stimulus, respondents are asked to evaluate the statements based on their perceptions and feelings toward the AI-generated images. This stimulus-based approach allows for controlled exposure to the experimental context before measurement. The collected responses are then subjected to a data cleaning process to remove incomplete or invalid entries, ensuring data quality and accuracy prior to analysis (Hair et al., 2019).

3.5 Data Analysis Techniques

The collected data are analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with the assistance of statistical software such as SmartPLS. SEM-PLS is selected due to its suitability for predictive research, its ability to handle complex structural models with mediating variables, and its robustness against non-normal data distributions [33], [34]. The analysis follows a

two-step approach. First, the measurement model (outer model) is evaluated to assess convergent validity, discriminant validity, AVE, and construct reliability. Second, the structural model (inner model) is examined to test hypothesized relationships using R^2 values, significance (hypothesis testing), and bootstrapping procedures to determine the statistical significance of path coefficients (Hair et al., 2019).

4. RESULTS AND DISCUSSION

4.1 Respondent Characteristics

Based on the data screening results, this study involved respondents relevant to the study context, namely, consumers with experience purchasing food online. Of the 212 initial respondents, 206 reported having purchased food online in the past six months through platforms such as GrabFood, GoFood, or other digital platforms. Next, age screening was conducted to ensure suitability for the research targets, namely millennials and Gen Z. Consequently, 204 respondents met the age criteria of 13–45 years and were included in the final sample for this study. This screening process was crucial to ensure that respondents had adequate digital literacy and exposure to technology to evaluate AI-based content.

Gender-wise, the majority of respondents 142 were female, while 62 were male. The predominance of female respondents suggests that women are more active in online food purchasing, particularly for daily consumption and culinary product exploration through digital platforms (Dominici et al., 2021). Furthermore, women generally have a higher level of engagement with visual content, particularly food-related content, making them more responsive when evaluating product appearance [40]. This indicates that perceptions of AI-generated images in this study are largely shaped by female consumers' perspectives, who are sensitive to aesthetics and visual authenticity [41].

By age group, the majority of respondents were young: 172 aged 13–28, 14 aged 18–28, and 18 aged 29–45. The dominance of this young age group indicates that this study is highly representative of Gen Z and early millennials, who are digital natives [42]. This group has a high level of exposure to technology, including artificial intelligence and digital visual content. Critically, this is relevant because younger generations tend to be more adaptable to technological innovations, but also more critical of content authenticity [4]. Therefore, they not only accept AI-generated images as innovations but also assess their authenticity and credibility before forming trust and developing purchasing intentions.

In terms of educational attainment, the majority of respondents 112 had a high school/vocational high school (SMA/SMK) or equivalent, followed by 79 with a bachelor's degree (S1/D4), 9 with a diploma (D1–D3), and 4 with a master's degree (S2). This distribution indicates that respondents are predominantly individuals with secondary to early tertiary education. Critically, this group generally possesses sufficient cognitive abilities to evaluate digital information, including the ability to distinguish between original and AI-generated content. This is important because perceptions of visual authenticity and perceived risk are highly dependent on an individual's ability to process information critically.

In terms of occupation, respondents were predominantly students 103, followed by 56 private sector employees, 18 homemakers, 12 freelancers, 10 self-employed, and 5 civil servants/military/police employees. The predominance of students reinforces the sample's characteristics as digital-savvy consumers with high levels of use of social media and other digital platforms.

Overall, the characteristics of the respondents in this study reflect the profile of modern digital consumers: the younger generation, and individuals with relatively good digital literacy. This implies that the research results are highly relevant in explaining consumer behavior in the era of AI-driven

marketing, particularly in the context of food product visualization. Furthermore, the dominance of Gen Z and millennials suggests that this study's findings are robust in representing the most active and influential market segments in today's digital ecosystem.

Table 1. Respondent Characteristics

Characteristics		Amount	%
Gender	Male	62	30.4%
	Female	142	69.6%
Usia	13-48 years	204	100%
Last Education	High School/Vocational High School	112	54.9%
	Diploma (D1-D3)	9	4.4%
	Bachelor's Degree (D4/S1)	79	38.7%
	Master's Degree (S2)	4	2.0%
Occupation	Freelance	12	5.9%
	IRT	18	8.8%
	Pegawai Negeri Sipil, TNI/POLRI	5	2.5%
	Pegawai Swasta	56	27.5%
	Pelajar/Mahasiswa	103	50.5%
	Wiraswasta	10	4.9%

Source: Processed primary data, 2026.

4.2 Inferential Analysis

An inferential test is a statistical technique used to draw conclusions or make predictions about a population based on data taken from a sample [43]. The goal is to determine whether the results obtained from the sample can be generalized/applied to the entire population/larger group. The analysis was conducted using SmartPLS version 4 software, which applies the Partial Least Squares (PLS) and variance-based Structural Equation Modeling (SEM) methods. PLS is a technique used to analyze the relationship between variables in a complex model, while SEM is used to test the cause-and-effect relationship between the variables involved. Figure 1 represents the latent variable model that will be analyzed in this study.

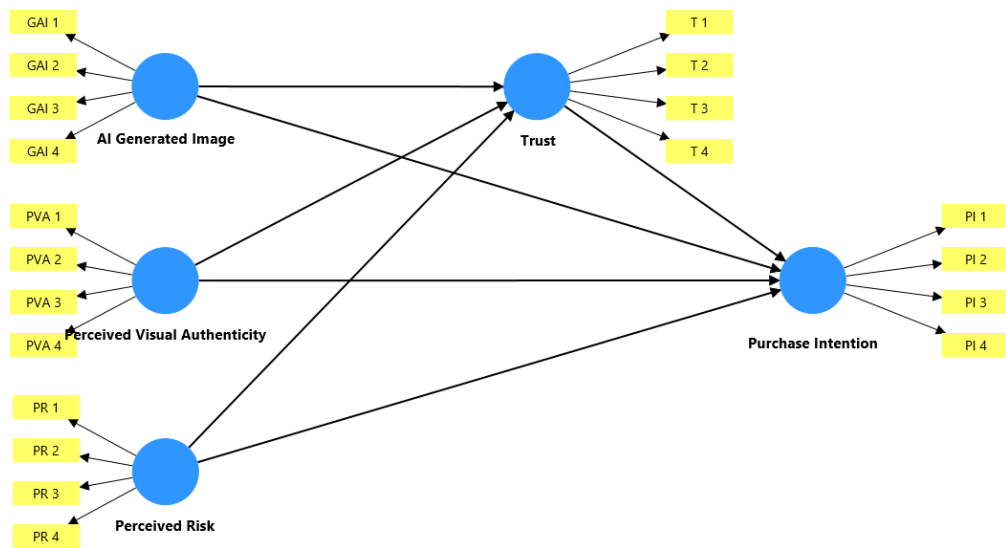


Figure 2. Latent Model of Research Variables.

There are two stages in testing a research model: the Outer Model and the Inner Model. The Outer Model focuses on the validity and reliability of the indicators used to measure latent variables, using Convergent Validity, Discriminant Validity, and Construct Reliability tests. The Inner Model focuses on the relationships between latent variables and tests the strength and significance of those relationships, using tests such as R^2 , path coefficients, and path significance.

1. Outer Model

The outer model focuses on the relationship between latent variables and indicators. Testing the outer model aims to ensure that the instruments used to measure the latent variables are valid and reliable. There are three main types of testing in the outer model: Convergent Validity, Discriminant Validity, and Construct Reliability [44].

a. Convergent Validity

Convergent Validity has two value criteria that can be evaluated, namely using the loading factor value or the Average Variance Extracted (AVE) value.

1) Loading Factor Value

The output of the outer loading estimation results is measured by the correlation between the indicator (instrument) score and its construct (variable). Indicators are considered valid if they have a correlation value above 0.70, or 0.6 is considered sufficient. Indicators that do not meet this requirement must be discarded. The results of the first stage of the convergent validity study are shown in Table 1.

Table 2. Outer Loading Results of Convergent Validity Test Stage 1

Pernyataan	AI Generated Image	Purchase Intention	Perceived Risk	Perceived Visual Authenticity	Trust	Ket
GAI 1	0.863					Valid
GAI 2	0.808					Valid
GAI 3	0.909					Valid
GAI 4	0.843					Valid
PI 1		0.931				Valid

PI 2	0.929	Valid
PI 3	0.912	Valid
PI 4	0.814	Valid
PR 1	0.867	Valid
PR 2	0.812	Valid
PR 3	0.909	Valid
PR 4	0.844	Valid
PVA 1	0.850	Valid
PVA 2	0.879	Valid
PVA 3	0.899	Valid
PVA 4	0.922	Valid
T 1	0.930	Valid
T 2	0.951	Valid
T 3	0.953	Valid
T 4	0.948	Valid

Source: Processed primary data, 2026.

The loading factor output of this first stage of testing shows that all statements for the variables AI-Generated Image, Perceived Risk, Perceived Visual Authenticity, Purchase Intention, and Trust have values >0.7 , making them valid. This indicates that the indicators/statements used successfully measure the correlation between the indicator/statement scores and the constructs/variables, thus supporting the construct validity of the measurement model.

2) Average Variance Extracted (AVE)

The output of the estimated average variance extracted (AVE) results can be seen in Table 3. A variable is said to be valid if it has an average variance extracted (AVE) value > 0.5 .

Table 3. AVE Results of Convergent Validity Test

Variabel	Average variance extracted	Keterangan
AI-Generated Image	0.734	Valid
Perceived Risk	0.737	Valid
Perceived Visual Authenticity	0.788	Valid
Purchase Intention	0.806	Valid
Trust	0.894	Valid

Source: Processed primary data, 2026.

The results of the Average Variance Extracted (AVE) test indicate that all variables in this study have met the convergent validity criteria, namely having an AVE value above 0.50. The AI-Generated Image variable obtained an AVE value of 0.734, Perceived Risk of 0.737, Perceived Visual Authenticity of 0.788, Purchase Intention of 0.806, and Trust of 0.894. These values indicate that each construct is able to explain more than 50% of the variance of the indicators that form it. Thus, it can be concluded that all variables in this

research model are declared convergently valid and suitable for use in further analysis on the structural model.

b. Discriminant Validity

Discriminant validity is used to ensure that the constructs or variables in a measurement model truly measure different things or do not overlap with each other. In other words, discriminant validity measures the extent to which different constructs in a measurement model can be distinguished from each other. Discriminant validity can be measured using one of three evaluation criteria; in this study, we used the cross-loading method..

1) Cross Loading

An indicator/statement is declared valid if its relationship with its construct/variable (cross-loading value) is higher than its relationship with other constructs. The following are the results of data processing using SmartPLS version 4 with cross-loading results as shown in the table below.

Table 4. Cross Loading Results of Discriminant Validity Test

Instrument	AI Generated Image	Perceived Risk	Perceived Visual Authenticity	Purchase Intention	Trust
GAI 1	0.863	0.867	-0.168	-0.230	-0.298
GAI 2	0.808	0.812	-0.079	-0.168	-0.194
GAI 3	0.909	0.909	-0.180	-0.259	-0.309
GAI 4	0.843	0.835	-0.209	-0.267	-0.306
PR 1	0.863	0.867	-0.168	-0.230	-0.298
PR 2	0.808	0.812	-0.079	-0.168	-0.194
PR 3	0.909	0.909	-0.180	-0.259	-0.309
PR 4	0.849	0.844	-0.200	-0.256	-0.295
PVA 1	-0.108	-0.103	0.850	0.476	0.489
PVA 2	-0.201	-0.196	0.879	0.596	0.662
PVA 3	-0.224	-0.222	0.899	0.581	0.598
PVA 4	-0.144	-0.142	0.922	0.591	0.624
PI 1	-0.214	-0.210	0.565	0.931	0.665
PI 2	-0.260	-0.256	0.578	0.929	0.645
PI 3	-0.234	-0.231	0.557	0.912	0.638
PI 4	-0.270	-0.265	0.568	0.814	0.878
T 1	-0.289	-0.284	0.647	0.707	0.930
T 2	-0.314	-0.309	0.623	0.725	0.951
T 3	-0.336	-0.332	0.664	0.778	0.953
T 4	-0.313	-0.308	0.617	0.831	0.948

Source: Processed primary data, 2026.

Discriminant validity was assessed using the cross-loading criterion to ensure that each indicator loads highest on its respective construct compared to other constructs. The

results indicate that all measurement items exhibit higher loadings on their corresponding latent variables than on other variables in the model.

Specifically, the indicators of AI-Generated Image (GAI1–GAI4) show the highest loadings on the AI-Generated Image construct, ranging from 0.808 to 0.909. Similarly, the indicators of Perceived Risk (PR1–PR4) load highest on the Perceived Risk construct, demonstrating strong construct representation. The indicators for Perceived Visual Authenticity (PVA1–PVA4) also exhibit the highest loadings on their respective constructs, ranging from 0.850 to 0.922.

Furthermore, the indicators of Purchase Intention (PI1–PI4) show strong loadings on their construct, ranging from 0.814 to 0.931, while the indicators of Trust (T1–T4) demonstrate the highest loadings on the Trust construct, ranging from 0.930 to 0.953. These results confirm that each indicator shares more variance with its assigned construct than with other constructs.

Therefore, it can be concluded that all constructs in this study meet the criteria for discriminant validity based on cross-loadings, indicating that the latent variables are empirically distinct and well-defined.

c. Construct Reliability

Construct reliability can be analyzed using one of two methods: Cronbach's alpha and composite reliability. Both methods are used to test the reliability of indicators within a variable.

1) Cronbach's Alpha

Cronbach's Alpha is an important indicator for testing the reliability of variables in a PLS-SEM model. A high Cronbach's Alpha value indicates that the construct/variable is measured well and consistently, ensuring measurement validity in PLS analysis. Conversely, a low Cronbach's Alpha value may indicate that the indicators/statements used are not reliable enough and need to be revised or replaced.

Table 5. Cronbach's Alpha Value

Variable	Cronbach's alpha	Ket.
AI-Generated Image	0.880	Reliabel
Perceived Risk	0.882	Reliabel
Perceived Visual Authenticity	0.911	Reliabel
Purchase Intention	0.920	Reliabel
Trust	0.961	Reliabel

Source: Processed primary data, 2026.

Cronbach's Alpha was used to assess the internal consistency reliability of the constructs. A Cronbach's Alpha value above 0.70 indicates acceptable reliability, while values above 0.80 indicate good reliability and values above 0.90 indicate excellent internal consistency (Hair et al., 2019).

The results show that all constructs meet the recommended threshold. Specifically, AI-Generated Image (GAI) has a Cronbach's Alpha of 0.880, Perceived Risk (PR) is 0.882, Perceived Visual Authenticity (PVA) is 0.911, Purchase Intention (PI) is 0.920, and Trust (T) is 0.961. These values indicate that all constructs demonstrate high internal consistency and reliability. Thus, it can be concluded that the measurement model satisfies the reliability requirements based on Cronbach's Alpha, and all constructs are considered reliable.

2) Composite Reliability

Composite Reliability is used to ensure the internal consistency of the indicators that form the latent variable. In Smart PLS, Composite Reliability is the primary tool for measuring reliability, and a CR value ≥ 0.7 is considered to meet the standards for research.

Table 6. Composite Reliability Values

Variabel	Cronbach's alpha	Ket.
AI-Generated Image	0.917	Reliabel
Perceived Risk	0.918	Reliabel
Perceived Visual Authenticity	0.937	Reliabel
Purchase Intention	0.943	Reliabel
Trust	0.971	Reliabel

Source: Processed primary data, 2026.

Construct reliability was assessed using Composite Reliability (CR) to evaluate the internal consistency of the measurement model. According to established guidelines, a Composite Reliability value above 0.70 indicates satisfactory reliability, while values above 0.90 indicate very high internal consistency (Hair et al., 2019).

The results show that all constructs exceed the recommended threshold. Specifically, AI-Generated Image (GAI) has a CR value of 0.917, Perceived Risk (PR) is 0.918, Perceived Visual Authenticity (PVA) is 0.937, Purchase Intention (PI) is 0.943, and Trust (T) reaches 0.971. These values indicate that all constructs demonstrate strong internal consistency and reliability.

Therefore, it can be concluded that the measurement model satisfies the reliability requirement, and all constructs are considered reliable for further analysis

2. Inner Model

The inner model in PLS-SEM describes the relationships between latent variables and is evaluated to determine the strength and significance of these relationships. The evaluation covers three main aspects: relationship significance (hypothesis testing), R-square, and hypothesis testing.

a. R Square (R^2)

The R-squared value in PLS-SEM measures how well the latent independent variables in a model explain the variability of the latent dependent variable. The R^2 value indicates the overall predictive power of the model. R^2 values range from 0 to 1, with higher values indicating a better model at explaining variance. The R-squared values in this analysis are as follows.

Table 7. Results of R Square (R^2) Test

	R-square	R-square adjusted
Purchase Intention	0.666	0.659
Trust	0.501	0.494

Source: Processed primary data, 2026.

Based on the analysis results obtained R-Square value of 0.666 for the Purchase Intention variable indicates that 66.6% of the variation in this variable can be explained by

the independent variables in the model, while 33.4% is influenced by other factors outside the model, so the relationship between the independent variables and Purchase Intention can be considered very strong. Meanwhile, the R-Square value of 0.501 for the Trust variable indicates that 50.1% of the variation in this variable can be explained by the independent variables in the model, with 49.9% influenced by external factors. This value indicates a fairly strong relationship, meaning the model is able to explain most of the factors that influence Trust, although there are still influences from outside the model. The following is an image of the PLS SEM Algorithm output to see the R² of the research model.

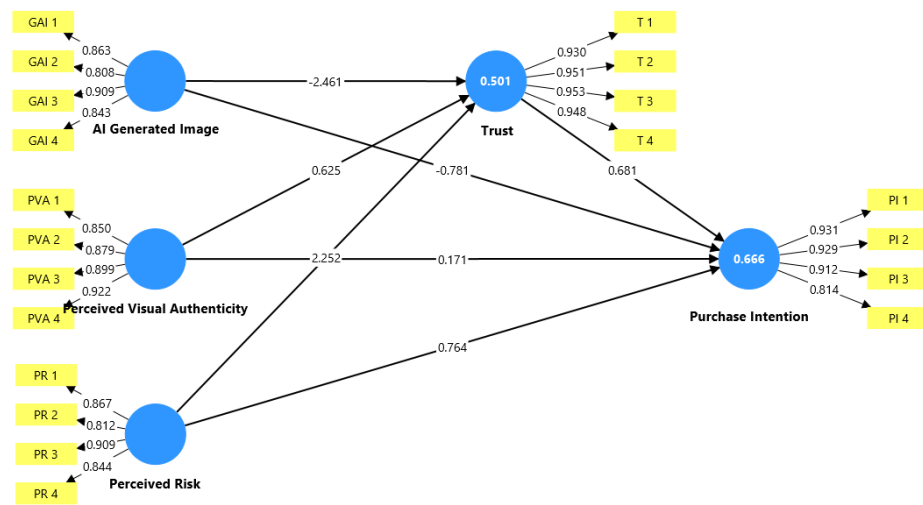


Figure 3. PLS SEM Algorithm model output

b. Significance (Hypothesis Testing)

The significance test for relationships in PLS-SEM is conducted to determine whether the relationship between latent variables in the model is statistically significant. This process typically uses a bootstrapping technique, where data is resampled to calculate the path coefficient and its standard error. The results are reported as a t-statistic or p-value.

A relationship is considered significant if the p-value is less than a predetermined significance level (in this study, a significance level of 0.05 was used). A significant path coefficient indicates that the relationship between the latent independent and dependent variables has strong statistical support, thus accepting the proposed hypothesis. The following are the bootstrapping results for the direct and indirect effect research models.

1) Bootstrapping results for the direct effect

The bootstrapping results for the direct effect can be seen in Table 7 as follows:

Table 8. Bootstrapping Path Coefficient Results for the Direct Effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV))	P values
AI Generated Image -> Purchase Intention	0.245	0.248	0.071	3.434	0.001
AI Generated Image -> Trust	0.280	0.284	0.054	5.228	0.000

Perceived Risk - > Purchase Intention	-0.000	-0.003	0.043	0.004	0.997
Perceived Risk - > Trust	-0.182	-0.181	0.055	3.332	0.001
Perceived Visual Authenticity -> Purchase Intention	0.204	0.197	0.084	2.423	0.015
Perceived Visual Authenticity -> Trust	0.495	0.495	0.057	8.620	0.000
Trust -> Purchase Intention	0.385	0.391	0.100	3.860	0.000

Source: Processed primary data, 2026.

Hypothesis testing in this study was conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with SmartPLS 4. The significance of relationships was evaluated using bootstrapping, with T-statistics and p-values examined. A relationship is considered significant when the T-statistic exceeds 1.96, and the p-value is below 0.05 [34].

The results indicate that AI-generated images have a positive and significant effect on purchase intention ($\beta = 0.245$, $T = 3.434$, $p = 0.001$). This finding suggests that AI-based visual content enhances consumers’ willingness to purchase. From a theoretical perspective, this can be explained by cue utilization theory, which holds that visual elements serve as extrinsic cues that influence consumer judgments. AI-generated visuals tend to be more optimized, aesthetically appealing, and tailored, thereby increasing perceived product value. This finding is consistent with prior studies that highlight that AI-generated image driven enhance the customer experience and influence purchase decisions [35]. More importantly, this study provides empirical evidence that AI-generated visuals can serve as effective persuasive cues within the S-O-R framework, directly triggering behavioral responses without necessarily requiring deeper cognitive evaluation. This indicates a shift in digital consumer behavior, where technologically enhanced visual stimuli are sufficient to activate purchase intention, reinforcing the growing dominance of AI-mediated visual communication in shaping consumer decision-making.

Furthermore, AI-generated images significantly influence trust ($\beta = 0.280$, $T = 5.228$, $p < 0.001$). This indicates that high-quality AI visuals can enhance perceived credibility. This result aligns with [45], who found that advanced technologies in marketing communication improve consumer trust, and [46], who emphasized that high-quality visual presentation strengthens perceived reliability. This finding demonstrates that AI-generated visual content can act not only as an aesthetic enhancement but also as a credibility-building mechanism within digital environments. This extends existing trust literature by showing that, in AI-driven

contexts, technological sophistication itself can serve as a signal of reliability, thereby reshaping the traditional basis of trust formation from purely human-generated authenticity to technologically mediated credibility.

In contrast, perceived risk does not significantly affect purchase intention ($\beta = -0.000$, $T = 0.004$, $p = 0.997$). This finding diverges from traditional studies [30], which suggest a negative relationship between perceived risk and purchase intention. A possible explanation lies in the evolving nature of digital consumer behavior. Modern consumers may experience risk normalization, where perceived risks are mitigated by familiarity with online platforms, reviews, and transactional safeguards [47]. As a result, perceived risk may no longer directly deter purchase intention. This finding suggests a structural shift in consumer decision-making, where perceived risk loses its role as a primary determinant of behavioral intention and instead becomes a secondary factor that operates through other psychological constructs, such as trust. This challenges conventional consumer behavior theories and indicates that, in AI-driven digital environments, consumers rely less on risk avoidance and more on trust-based evaluation when forming purchase intentions.

Nevertheless, perceived risk has a negative and significant effect on trust ($\beta = -0.182$, $T = 3.332$, $p = 0.001$). This suggests that while risk may not directly influence purchase intention, it undermines trust, thereby affecting decision-making. This finding supports previous research indicating that perceived risk is a key antecedent of trust in online environments [48], [49]. Therefore, perceived risk operates indirectly, highlighting the mediating role of trust. This result confirms that trust functions as a critical psychological buffer that absorbs the negative impact of perceived risk, rather than allowing risk to directly shape behavioral intention. This finding refines the S-O-R framework by demonstrating that, in AI-driven digital contexts, perceived risk is structurally repositioned as an antecedent of trust rather than a direct predictor of purchase intention, reinforcing the central role of trust as the primary mechanism through which uncertainty is managed in consumer decision-making.

Moreover, perceived visual authenticity positively and significantly affects purchase intention ($\beta = 0.204$, $T = 2.423$, $p = 0.015$). This indicates that consumers are more likely to purchase products when visuals are perceived as authentic. This finding is consistent with Bui et al., (2024), who argued that authenticity enhances consumer engagement and behavioral intention. More importantly, this finding highlights that visual authenticity functions as a direct heuristic cue in consumer decision-making, enabling consumers to form purchase intentions without extensive cognitive evaluation. This extends the S-O-R framework by demonstrating that, in AI-generated visual contexts, authenticity is not merely an aesthetic attribute but a critical determinant of behavioral response, reinforcing its role as a key driver of consumer action in digitally mediated environments.

Additionally, perceived visual authenticity has a strong positive effect on trust ($\beta = 0.495$, $T = 8.620$, $p < 0.001$), making it one of the most influential predictors in the model. This highlights that authenticity plays a critical role in building consumer trust. [50] similarly found that perceived visual authenticity significantly contributes to brand trust. In the context of AI-generated content, this finding reveals an important paradox: while AI enhances visual quality, it may simultaneously increase consumer skepticism if authenticity is questioned. These findings position

visual authenticity not merely as an aesthetic attribute, but as a cognitive validation mechanism that determines the success of technology integration in digital marketing. This suggests that consumer trust in visual sophistication is not automatic, but rather depends on the extent to which the AI representation can maintain "functional similarity" to the reality of the promised product. Therefore, this study makes a theoretical contribution by confirming that, in the era of synthetic content, the perception of authenticity remains a fundamental pillar that moderates information uncertainty and strengthens brand legitimacy in consumers' eyes.

Finally, trust significantly influences purchase intention ($\beta = 0.385$, $T = 3.860$, $p < 0.001$), confirming its role as a key determinant in consumer decision-making. This result is consistent with the established literature, which emphasizes trust as a central factor in online purchasing behavior [51], [52]. Trust functions as a risk-reduction mechanism that enables consumers to proceed with transactions despite uncertainty. These findings confirm that in the context of AI-based marketing, trust acts as a "psychological bridge" that validates technological stimuli before they are transformed into behavioral intentions. This confirms that the sophistication of generative algorithms will not reach their peak conversion potential without the assurance of brand integrity perceived by consumers. Therefore, this study contributes to the marketing management literature by establishing that, in an increasingly machine-mediated digital ecosystem, trust remains the primary currency moderating the relationship between visual innovation and economic decisions, while also serving as a key antidote to the information ambiguity posed by AI-generated content.

Overall, the findings suggest that most hypotheses are supported, except for the direct relationship between perceived risk and purchase intention. Importantly, this study highlights a shift in consumer behavior in the AI-driven digital context, where visual perception and authenticity play a more dominant role than perceived risk, and trust serves as a central mediating mechanism.

2) Bootstrapping results of indirect effects (indirect effects)

The results of bootstrapping the indirect effect can be seen in Table 8 as follows:

Table 9. Results of Path Coefficient Bootstrapping Indirect Effect

Path Coefficient	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values	Ket.
AI Generated Image -> Trust -> Purchase Intention	0.267	0.272	0.111	2.410	0.008	Valid
Perceived Risk -> Trust -> Purchase Intention	-0.036	-0.035	0.018	1.949	0.026	Valid
Perceived Visual Authenticity -	0.003	0.005	0.025	0.123	0.451	Not Valid

> Trust ->
Purchase
Intention

Source: Processed primary data, 2026.

The indirect effect analysis was conducted using the bootstrapping procedure in SEM-PLS to examine the mediating role of trust in the relationship between exogenous variables and purchase intention. A mediation effect is considered significant when the indirect path shows a T-statistic > 1.96 and a p-value < 0.05 [34]

The results indicate that AI-generated images have a positive and significant indirect effect on purchase intention through trust ($\beta = 0.267$, $T = 2.410$, $p = 0.008$). This finding confirms that trust mediates the impact of AI-generated visuals on consumer purchase intention. This result is consistent with recent studies showing that AI-driven content influences consumer behavior primarily through trust-building mechanisms rather than through direct effects alone [53], [54]. For instance, research on AI-powered personalization demonstrates that trust significantly mediates the relationship between AI-based features and purchase intention [55].

Critically, this suggests that the effectiveness of AI-generated images is not merely due to their visual appeal, but also to their ability to enhance perceived credibility and reduce uncertainty. However, prior studies also highlight a potential paradox: while AI-generated content can increase efficiency and personalization, it may simultaneously trigger skepticism when consumers are aware of its artificial origin [56], [57]. Thus, the mediating role of trust becomes crucial in converting visual perception into actual behavioral intention.

Furthermore, the findings show that perceived risk has a negative, significant indirect effect on purchase intention through trust ($\beta = -0.036$, $t = 1.949$, $p = 0.026$). This indicates that perceived risk reduces purchase intention indirectly by weakening consumer trust [58]. This result reinforces the argument that, in digital environments, perceived risk operates more as a precursor of trust than as a direct determinant of behavioral intention.

This finding aligns with contemporary research emphasizing that trust acts as a key mediator in online consumer behavior, particularly in technology-driven contexts [59]. From a critical perspective, this implies that consumers do not necessarily abandon purchase decisions due to risk; instead, they rely on trust as a psychological mechanism to compensate for uncertainty [59]. Therefore, when trust remains intact, the negative effect of perceived risk on purchase intention can be minimized.

Interestingly, perceived visual authenticity did not show a significant indirect effect on purchase intention through trust ($\beta = 0.003$, $T = 0.123$, $p = 0.451$). This suggests that while visual authenticity can enhance trust, its effect on purchase intention is not always mediated by trust [60]. Overall, these findings highlight that Trust plays a crucial mediating role in translating technological cues and risk perceptions into consumer behavioral intentions. However, its mediating role is not universally applicable across all antecedents, particularly in the case of perceived visual authenticity.

5. CONCLUSION

This study aims to examine consumer responses to AI-generated food images by integrating perceived visual authenticity, perceived risk, and trust within the Stimulus–Organism–Response (S-O-R) framework. The findings reveal that AI-generated images significantly enhance both trust and purchase intention, indicating that AI-based visual content can function as an effective marketing stimulus when properly managed.

Furthermore, perceived visual authenticity emerges as the strongest determinant of trust and directly influences purchase intention, highlighting the critical role of realistic, credible visual representation in digital food marketing. In contrast, perceived risk does not directly affect purchase intention; however, it negatively influences trust, which in turn shapes consumer intention. This finding suggests that perceived risk operates indirectly through trust rather than acting as a primary decision-making factor.

Importantly, this study confirms the mediating role of trust in the relationship between AI-generated images and purchase intention, as well as between perceived risk and purchase intention. However, trust does not mediate the relationship between perceived visual authenticity and purchase intention, suggesting that authenticity serves as a direct heuristic cue in consumer decision-making.

Overall, this research contributes to the literature by demonstrating a shift in consumer behaviour in AI-driven marketing contexts, where visual perception and trust play more dominant roles than perceived risk. In practice, the findings imply that businesses should prioritise authentic, transparent AI-generated visuals to strengthen consumer trust and enhance purchase intention. Additionally, managing perceived risk through trust-building strategies becomes essential to ensure positive consumer responses in digital environments.

More importantly, this study provides a clear theoretical contribution by extending the Stimulus–Organism–Response (S-O-R) framework in the context of AI-driven visual marketing. The findings demonstrate a structural shift in consumer decision-making, in which perceived visual authenticity serves as a dominant stimulus that can directly trigger behavioral responses, while perceived risk loses its direct explanatory power and operates primarily through trust. This indicates that, in AI-mediated environments, trust acts as a central psychological mechanism that absorbs uncertainty, whereas authenticity serves as a critical heuristic cue that simplifies decision-making processes. Consequently, this research challenges traditional consumer behavior assumptions that emphasize risk as a primary determinant of purchase intention. Instead, it highlights the increasing importance of authenticity- and trust-based evaluations in shaping consumer responses to AI-generated content.

REFERENCES

- Ali, L., Ali, F., Abdalla, M. J., & Alotaibi, S. (2025). Beyond the hype: Evaluating the impact of generative AI on brand authenticity, image, and consumer behavior in the restaurant industry. *International Journal of Hospitality Management*, *131*, 104318. <https://doi.org/10.1016/j.ijhm.2025.104318>
- Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., & Dwivedi, Y. K. (2024). The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *International Journal of Information Management*, *79*, 102759. <https://doi.org/10.1016/j.ijinfomgt.2024.102759>
- Arruda Filho, E. J. M., Simões, J. D. S., & De Muylder, C. F. (2020). The low effect of perceived risk in the relation between hedonic values and purchase intention. *Journal of Marketing Management*, *36*(1–2), 128–148. <https://doi.org/10.1080/0267257X.2019.1697725>
- Aryani, D. N., Nair, R. K., Hoo, D. X. Y., Hung, D. K. M., Lim, D. H. R., Chandran, D. A. R., Chew, W. P., & Desai, A. (2021). A Study on Consumer Behaviour: Transition from Traditional Shopping to Online Shopping During the COVID-19 Pandemic. *International Journal of Applied Business and International Management*, *6*(2), 81–95. <https://doi.org/10.32535/ijabim.v6i2.1170>

- Asadoorian, O. M., & Demetri, K. (2009). *Essentials of Inferential Statistics* (5th ed.). University Press of America.
- Bodó, B. (2021). Mediated trust: A theoretical framework to address the trustworthiness of technological trust mediators. *New Media & Society*, 23(9), 2668–2690. <https://doi.org/10.1177/1461444820939922>
- Boo, C. (2025). When customer meets AI failure: expectation discrepancy perspective. *Applied Economics Letters*, 32(7), 1039–1043. <https://doi.org/10.1080/13504851.2023.2300973>
- Bui, H. T., Filimonau, V., & Sezerel, H. (2024). AI-thenticity: Exploring the effect of perceived authenticity of AI-generated visual content on tourist patronage intentions. *Journal of Destination Marketing & Management*, 34, 100956. <https://doi.org/10.1016/j.jdmm.2024.100956>
- Chen, H., Liu, S., Wang, Y., Dong, N., Kim, W. G., & Li, J. (Justin). (2025). Tainted by technology? The effect of AI-generated image labels on consumers' food purchase intentions. *British Food Journal*, 1–17. <https://doi.org/10.1108/BFJ-08-2025-1101>
- Cinelli, M. D., & LeBoeuf, R. A. (2020). Keeping It Real: How Perceived Brand Authenticity Affects Product Perceptions. *Journal of Consumer Psychology*, 30(1), 40–59. <https://doi.org/10.1002/jcpsy.1123>
- Creswell, J. W., & Creswell, J. D. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. Sage.
- Dawes, J. (2008). Do Data Characteristics Change According to the Number of Scale Points Used? An Experiment Using 5-Point, 7-Point and 10-Point Scales. *International Journal of Market Research*, 50(1), 61–104. <https://doi.org/10.1177/147078530805000106>
- De, O., Simanjuntak, P., Purba, R. R., & Sarah, E. M. (2025). Indonesian Institute for Counseling, Education and Therapy The role of influencer marketing moderation in consumer journeys and digital trust in online purchasing decisions. *Jurnal Konseling Dan Pendidikan*, 13. <https://doi.org/10.29210/1169100>
- Dhiman, R., & Bhati, N. S. (2025). When AI meets influencers: Role of AI-powered instagram influencers driving consumers' purchase intentions: An integration of SMIV & SOR framework. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(3), 100591. <https://doi.org/10.1016/j.joitmc.2025.100591>
- Djimesah, I. E., Zhao, H., Okine, A. N. D., Gyamfi, C. A., Mireku, K. K., Chen, W., Duah, E., & Osei-Mensah, E. (2026). Digital infrastructure, trust, and behavioral intention: An extended technology acceptance model for crowdfunding adoption in emerging economies. *Strategic Business Research*, 2(1), 100068. <https://doi.org/10.1016/j.sbr.2026.100068>
- Du, H., Li, Z., Niyato, D., Kang, J., Xiong, Z., Shen, X., & Kim, D. I. (2024). Enabling AI-Generated Content Services in Wireless Edge Networks. *IEEE Wireless Communications*, 31(3), 226–234. <https://doi.org/10.1109/MWC.004.2300015>
- Furner, C. P., Drake, J. R., Zinko, R., & Kisling, E. (2022). Online Review Antecedents of Trust, Purchase, and Recommendation Intention: A Simulation-Based Experiment for Hotels and AirBnBs. *Journal of Internet Commerce*, 21(1), 79–103. <https://doi.org/10.1080/15332861.2020.1870342>
- Ghaith, M. M., Al-rawashdeh, G. H., Alzuod, M. A., Ghaith, Y. M., Alotoum, F. J., AlSokkar, A. A. M., Al-Gasawneh, J., & Alghizzawi, M. (2024). Examining the Effects of Digital Payment and Impulsive Buying on Purchase Intention. *2024 2nd International Conference on Cyber Resilience (ICCR)*, 1–7. <https://doi.org/10.1109/ICCR61006.2024.10532804>
- Gkikas, D. C., & Theodoridis, P. K. (2022). *AI in Consumer Behavior* (pp. 147–176). https://doi.org/10.1007/978-3-030-80571-5_10
- Goulding, C., & Derbaix, M. (2019). Consuming material authenticity in the age of digital reproduction. *European Journal of Marketing*, 53(3), 545–564. <https://doi.org/10.1108/EJM-10-2017-0717>
- Güleç, H., & Özkaya, F. (2025). Food styling and food photography with generative AI. *Journal of Tourism Leisure and Hospitality*, 6(2), 90–103. <https://doi.org/10.48119/teleho.1573824>
- Habbal, A., Ali, M. K., & Abuzaraida, M. A. (2024). Artificial Intelligence Trust, Risk and Security Management (AI TRiSM): Frameworks, applications, challenges and future research directions. *Expert Systems with Applications*, 240, 122442. <https://doi.org/10.1016/j.eswa.2023.122442>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31.
- Hanaysha, J. R., Ramadan, H. I., & Alhyasat, K. M. K. (2025). Exploring the impact of customer reviews, website quality, perceived service quality, and product assortment on online purchase intention: The mediating role of trust. *Telematics and Informatics Reports*, 19, 100236. <https://doi.org/10.1016/j.teler.2025.100236>

- Hipólito, F., Dias, Á., & Pereira, L. (2025). Influence of Consumer Trust, Return Policy, and Risk Perception on Satisfaction with the Online Shopping Experience. *Systems*, 13(3), 158. <https://doi.org/10.3390/systems13030158>
- Huang, Y., & Mohamad, S. H. (2026). Unveiling how nano live streamers boost consumer purchase intention: The mediating role of trust in nano live streamer using PLS-SEM. *Acta Psychologica*, 263, 106345. <https://doi.org/10.1016/j.actpsy.2026.106345>
- Kaur, S., & Arora, S. (2020). Role of perceived risk in online banking and its impact on behavioral intention: trust as a moderator. *Journal of Asia Business Studies*, 15(1), 1–30. <https://doi.org/10.1108/JABS-08-2019-0252>
- Khan, A., Khan, Z., & Nabi, M. K. (2024). “I think exactly the same”—trust in SMIs and online purchase intention: a moderation mediation analysis using PLS-SEM. *Journal of Advances in Management Research*, 21(2), 311–330. <https://doi.org/10.1108/JAMR-03-2023-0087>
- 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. <https://doi.org/10.1002/mar.21498>
- Kim, J.-H., & Song, H. (2020). The influence of perceived credibility on purchase intention via competence and authenticity. *International Journal of Hospitality Management*, 90, 102617. <https://doi.org/10.1016/j.ijhm.2020.102617>
- Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227–261. <https://doi.org/10.1111/isj.12131>
- Lăzăroiu, G., Neguriță, O., Grecu, I., Grecu, G., & Mitran, P. C. (2020). Consumers’ Decision-Making Process on Social Commerce Platforms: Online Trust, Perceived Risk, and Purchase Intentions. *Frontiers in Psychology*, 11. <https://doi.org/10.3389/fpsyg.2020.00890>
- Lee, J., & Lim, H. (2023). Visual aesthetics and multisensory engagement in online food delivery services. *International Journal of Retail & Distribution Management*, 51(8), 975–990. <https://doi.org/10.1108/IJRDM-09-2021-0451>
- Li, L., He, L., Gooi, L.-M., & Chong, K. M. (2025). Trust to repurchase: investigating consumer behaviour with SOR theory and dual-stage SEM-ANN analysis. *Asia Pacific Journal of Marketing and Logistics*, 1–15. <https://doi.org/10.1108/APJML-02-2025-0303>
- Lyu, M., & Huang, Q. (2024). Visual elements in advertising enhance odor perception and purchase intention: The role of mental imagery in multi-sensory marketing. *Journal of Retailing and Consumer Services*, 78, 103752. <https://doi.org/10.1016/j.jretconser.2024.103752>
- Maares, P., Banjac, S., & Hanusch, F. (2021). The labour of visual authenticity on social media: Exploring producers’ and audiences’ perceptions on Instagram. *Poetics*, 84, 101502. <https://doi.org/10.1016/j.poetic.2020.101502>
- Malhotra, G., & Ramalingam, M. (2025). Perceived anthropomorphism and purchase intention using artificial intelligence technology: examining the moderated effect of trust. *Journal of Enterprise Information Management*, 38(2), 401–423. <https://doi.org/10.1108/JEIM-09-2022-0316>
- Mathayomchan, B., & Taecharunroj, V. (2020). “How was your meal?” Examining customer experience using Google maps reviews. *International Journal of Hospitality Management*, 90, 102641. <https://doi.org/10.1016/j.ijhm.2020.102641>
- Murtarelli, G., Romenti, S., & Valentini, C. (2022). The impact of digital image-based features on users’ emotions and online behaviours in the food industry. *British Food Journal*, 124(1), 31–49. <https://doi.org/10.1108/BFJ-12-2020-1099>
- Naci Çoklar, A., & Tatli, A. (2021). Examining the Digital Nativity Levels of Digital Generations: From Generation X to Generation Z. *Shanlax International Journal of Education*, 9(4), 433–434. <https://doi.org/10.34293/education.v9i4.4224>
- Nazrin, N., Isahak Merican, F. M., Taharuddin, N. S., & Ibrahim, N. I. (2025). How AI-Generated Images Impact Consumer Perceptions and Brand Identity. *Ideology Journal*, 10(1). <https://doi.org/10.24191/idealogy.v10i1.780>
- Ou, M., Zheng, H., Zeng, Y., & Hansen, P. (2026). Trust it or not: Understanding users’ motivations and strategies for assessing the credibility of AI-generated information. *New Media & Society*, 28(2), 507–529. <https://doi.org/10.1177/14614448241293154>

- Pappas, N. (2016). Marketing strategies, perceived risks, and consumer trust in online buying behaviour. *Journal of Retailing and Consumer Services*, 29, 92–103. <https://doi.org/10.1016/j.jretconser.2015.11.007>
- Punyatoya, P. (2019). Effects of cognitive and affective trust on online customer behavior. *Marketing Intelligence & Planning*, 37(1), 80–96. <https://doi.org/10.1108/MIP-02-2018-0058>
- Rister Portinari Maranca, A., Chung, J., Hinck, M., Wolsky, A. D., Egami, N., & Stewart, B. M. (2025). Correcting the Measurement Errors of AI-Assisted Labeling in Image Analysis Using Design-Based Supervised Learning. *Sociological Methods & Research*, 54(3), 984–1016. <https://doi.org/10.1177/00491241251333372>
- Rohden, S. F., & Zeferino, D. G. (2023). Recommendation agents: an analysis of consumers' risk perceptions toward artificial intelligence. *Electronic Commerce Research*, 23(4), 2035–2050. <https://doi.org/10.1007/s10660-022-09626-9>
- Salih, S., Husain, O., Mohamed Almohamedh, R., tajelsier, H., Hassan Abdalla Hashim, A., Elshafie, H., & Motwakel, A. (2026). From ideation to execution: Unleashing the power of generative AI in modern digital marketing and customer engagement- A systematic literature review and case study. *Array*, 29, 100630. <https://doi.org/10.1016/j.array.2025.100630>
- Sekaran, U., & Bougie, R. (2018). *Metode Penelitian untuk Bisnis* (3rd ed.). Salemba Empat.
- Sharma, G., & Lal, Prof. (Dr.) R. (2024). Ethical Considerations in the Use of AI-Generated Images in Advertising: Balancing Innovation and Responsibility. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4998132>
- Sinha, N., Roy Chaudhuri, H., Fowler, J. G., & Mazumdar, S. (2018). Market-mediated authenticity in culturally themed culinary space. *Qualitative Market Research: An International Journal*, 21(3), 353–374. <https://doi.org/10.1108/QMR-07-2016-0059>
- Sweeney, J. C., Soutar, G. N., & Johnson, L. W. (1999). The role of perceived risk in the quality-value relationship: A study in a retail environment. *Journal of Retailing*, 75(1), 77–105. [https://doi.org/10.1016/S0022-4359\(99\)80005-0](https://doi.org/10.1016/S0022-4359(99)80005-0)
- Vafaei-Zadeh, A., Nikbin, D., Wong, S. L., & Hanifah, H. (2025). Investigating factors influencing AI customer service adoption: an integrated model of stimulus–organism–response (SOR) and task-technology fit (TTF) theory. *Asia Pacific Journal of Marketing and Logistics*, 37(6), 1465–1502. <https://doi.org/10.1108/APJML-05-2024-0570>
- Valentini, C., Romenti, S., Murtarelli, G., & Pizzetti, M. (2018). Digital visual engagement: influencing purchase intentions on Instagram. *Journal of Communication Management*, 22(4), 362–381. <https://doi.org/10.1108/JCOM-01-2018-0005>
- Ventre, I., & Kolbe, D. (2020). The Impact of Perceived Usefulness of Online Reviews, Trust and Perceived Risk on Online Purchase Intention in Emerging Markets: A Mexican Perspective. *Journal of International Consumer Marketing*, 32(4), 287–299. <https://doi.org/10.1080/08961530.2020.1712293>
- Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science*, 44(1), 119–134. <https://doi.org/10.1007/s11747-015-0455-4>
- Wang, Z. (2025). The influence of AI on consumer behavior: Shaping choices and preferences in the digital marketplace. *Systems and Soft Computing*, 7, 200397. <https://doi.org/10.1016/j.sasc.2025.200397>
- Wu, M., Yong, K. M., & Yuen, K. F. (2026). The personalisation paradox: How generative AI shapes conservation intentions through emotional and cognitive pathways. *Journal of Innovation & Knowledge*, 15, 100993. <https://doi.org/10.1016/j.jik.2026.100993>
- Yang, J., Teran, C., Battocchio, A. F., Bertellotti, E., & Wrzesinski, S. (2021). Building Brand Authenticity on Social Media: The Impact of Instagram Ad Model Genuineness and Trustworthiness on Perceived Brand Authenticity and Consumer Responses. *Journal of Interactive Advertising*, 21(1), 34–48. <https://doi.org/10.1080/15252019.2020.1860168>
- Yuniarty, Ikhsan, R. B., & Ohliati, J. (2020). E-WOM And Social Commerce Purchase Intentions: Applying The Theory of Planned Behavior. *2020 International Conference on Information Management and Technology (ICIMTech)*, 34–39. <https://doi.org/10.1109/icimtech50083.2020.9211256>
- Ziakis, C., & Vlachopoulou, M. (2023). Artificial Intelligence in Digital Marketing: Insights from a Comprehensive Review. *Information*, 14(12), 664. <https://doi.org/10.3390/info14120664>