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Underlying Mechanisms of Consumer Reactions to Human vs Ai Generated Brand Identity

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Abstract

Applications of artificial intelligence have gradually increased with the high-speed development of AI technology. Generative AI, is a form of AI applications which differs from other AI technologies by being able to create original and novel contents, like images, texts, videos etc. In the last couple of years, this rapid development has transformed many businesses and processes, especially the digital marketing and communications. Marketing and branding areas have integrated artificial intelligence applications to their processes and outputs mainly to increase the number of outputs, to decrease the human force need and to gain from time. The tasks assigned to artificial intelligence are like forming a brand's identity, creating images for a brand, or composing advertisements. As the portion of using GenAI applications on brand activities increases, questions to understand how efficient and effective GenAI usage is in marketing and branding activities rise, as a natural result. This study investigates how AI-generated brand identity elements influence consumer's perceptions of a brand and how does it affect consumers' behavioural intentions, by employing a survey-based research design, participants are exposed to both GenAI generated and human designer created visuals to conceive a comparative experience between these two different approaches on the same task.

Keywords: Branding, Brand Image, Brand Identity, Consumer Behaviour, Generative AI

1. Introduction

The entry of AI to the market changed the dynamics of business (Yuan et al., 2022). With the rapid development of AI, businesses gain new approaches on their classical methods. According to researches, usage of AI shortened the time and effort needed to achieve a certain goal, via automating the jobs (Yuan et al., 2022). As it eases most of the routine works up, businesses wanted to use it more frequently than it was on their works.

Businesses used AI to automate their processes, to reduce the errors due to human factor and keep the customer experience on a certain level with minimum labor force needed. AI applications are also useful to obtain an adequate brand image to have an important advantage on competition with rivals. The idea of having a more important and straight influence on consumers with using AI is defended by the same study of Yuan et al. (2022).

2. Generative AI

With the introduction of GenAI to marketing applications, the perspective of using AI has gone further than only analytic purposes and automation, but also to use in content generation (Park & Ahn, 2024).

GenAI tools like DALL-E and Midjourney can create art and design from textual input. DALL-E also can propose a guideline to create a graphic design manually by offering tools to use, techniques to apply.

2.1 Artificial Intelligence Applications on Branding and Marketing

Capabilities of GenAI makes it a useful tool to benefit from. Also, the enthusiasm which both the brand and consumer side feel against technological developments, is a known fact by the market (Deryl et al., 2023).

By 2025, GenAI is predicted to produce almost 33 percent of major brands' marketing messages (Gartner, 2023, as cited in Brüns & Meißner, 2024). Almost 63% of the brands are applying GenAI approaches on their marketing activities, but there are significant drawbacks about the usage of GenAI (Robitaille, 2024).

Despite it facilitates creating a brand with zero graphic-design background needed, effect of the AI designs on consumers are unknown. The difference between an AI generated logo and a human-designed logo shown together, is still recognizable. WFA research shows that brands are still sceptical about the utilization of contents, created by AI (Robitaille, 2024).

Recent papers offered different conceptual frameworks for AI usage in businesses. Deryl et al. (2025) developed an eight-dimensional framework to structure AI implementation in branding strategy, by reviewing 419 articles. Trust is one of these dimensions, enabling competitive advantage and boosting lasting consumer relationships. Grewal et al. (2025), offer a four-quadrant framework that facilitates the human-GenAI collaboration. Paper underlines human augmentation and input type are key factors when implementing GenAI in companies' processes, requiring managers to balance the associated risks of using GenAI.

2.2 Brand Authenticity and Consumer Reactions to AI Applications

Different studies pointed to the aversion against AI usage. Zehnle et al. (2025), underline that many studies pointing out a relentless AI aversion toward AI applications, despite the fact that AI usage is rapidly increasing. However, it is also indicated that this aversion is not stationary, like when the first time Generative AI applications get popular there was a null effect but after a while with the concerns about artificial intelligence usage and its social effect, the worries heighten. After a while, the concerns get lower and nowadays people even uses AI as "companions" in daily routine (Zehnle et al., 2025).

With the increase of GenAI usage on the marketing activities, perceptions of the consumers for the brands' gets worsen, with proposing that using GenAI decreases the authenticity of the brand and it causes a fall for the brand perception of consumers. It affects brand behaviour and creates negative consumer reactions (Brüns & Meissner, 2024).

Disclosure of AI raises the question of whether "AI-Generated" label should be provided to the customers. Patil and Rice's (2026) study showed that the effect of AI disclosure on perceived effort arises specifically with the presence of human-involvement, despite AI disclosure having no direct negative effect on product quality perceptions. In parallel, findings from Gu et al. (2026) underlines that AI disclosure negatively impacts brand attitudes consistently. Ali et al.

(2025) also underline the negative impression on AI usage in marketing and branding studies, indicating human factor is still important in branding activities within restaurant sector.

Findings mentioned above suggest humans still keep an important place in marketing since AI still lacks skills and features which humans have. Nevertheless, utilization of Generative AI is growing. According to the research of WFA, only 9% of the brands state that they do not have a planning about applying to GenAI on their marketing activities (Robitaille, 2024).

Furthermore, human-likeness cue has an inverted U-shaped pattern on brand outcomes, according to Guo et al. (2025). Applying it excessively may influence the brand negatively, since emotional responses of virtual entities on social media have authenticity deficits (Guo et al., 2025). In the experiment of Park & Ahn (2024) brand personality generated with traditional methods is more convenient than AI-Generated brand personalities.

3. Theoretical Framework

3.1 Brand Image

Brand image is the perception of consumers of brand characteristics and caliber of products. When a consumer encounters with a reputable logo, the first thing comes to mind is the attributes and properties about the brand, product and services (Cui et al., 2024). Having a strong brand image on the other hand, may also give the chance of having a higher market share, setting higher prices on products and etc. to the brands (Yuan et al. 2022).

H1. A better brand image directly affects the consumer behaviour toward the brand positively.

3.2 Consumer – Brand Congruence

Brand identification may boost the purchasing intention. This tops, when a consumer connects a likeliness with the brand. As congruity increases, consumer's behaviours get better (Taylor et al., 2011). Consumers do purchase the product from brands that they align themselves more, rather than other brands (Raji et al., 2019).

In the experiment, survey assessed consumer-brand identification through pet ownership. Since the experiment included a mobile app to connect pet owners, it is expected that pet owners would engage better.

H2. Consumer-brand congruity positively affects brand image and the purchasing intention.

3.3 Visual Complexity

Visual complexity describes the number of components in a view or in an image and the level of details that these components transmit (Deng, Poole, 2010 as cited in Kusumasondjaja & Tjiptono, 2019). It can affect consumer perceptions and consumer behaviours, such as purchasing behaviour (Kusumasondjaja & Tjiptono, 2019). Many researches support that complex promotions are more likely to gather better consumer reactions (Kusumasondjaja & Tjiptono, 2019).

H3. Visual complexity positively affects the purchasing intention.

3.4 Informativeness

An advertisement may be referred as informative, if it can transmit the important information or facts, in a clear way, to the consumer (Moldovan et al., 2019).

Taylor et al. (2011) underlines that informativeness positively affect the advertisement performance. Purchasing behaviour is positively affected according to the researches, by extensive and high-quality information that is provided in commercials (Shao et al., 2024).

H4. Better informative characteristics of the advertisement affects the purchasing intention positively.

3.5 Entertainment

According to Yang et al. (2013), entertainment is an intrinsic drive for information technology usage. Therefore, it may be accepted as a motivator for advertisements published via technological devices. Entertainment has a significant effect on social media advertisements (Alalwan, 2018).

H5. Entertainment traits of the advertisement affects the purchasing intention positively.

3.6 Reliability

An advertisement can be referred as reliable, if the consumers think it is honest and sincere (Yang et al., 2013). It can boost the effect of advertisements, with making consumer feel safe (Shao et al., 2024), and may have a substantial influence on consumers' decision on purchase (Yang et al., 2013).

H6. Reliability is a booster for advertisements, which affects the purchasing intention positively.

4. Methods

To examine how AI usage affects brand image and consumer purchasing decisions, a survey was conducted with 261 participants (min. N=119, given effect size = 0.15 and alpha = 0.05 applying Linear Multiple Regression, fixed model and R^2 increase using G*Power). Participants were limited to people who are older than the age of 18.

Measurement used a five-point likert scale, along a few multiple-choice questions. Ethical approval for the questionnaire was granted by Istanbul Technical University Ethics Committee. All participants were presented a consent statement on the top of the questionnaire. The questionnaire consisted 74 questions, including demographical questions. Answers are collected anonymously without keeping the participants' data.

Questionnaire was distributed and collected via Google Forms in Türkiye over a limited time. To expand the sample progressively, snow-ball sampling method has been used. Data were analyzed in IBM SPSS 30. To test the hypotheses' reliability analysis, factor analysis, one-way ANOVA and independent sample t-test methods are applied.

To compare GenAI designs and human-generated designs, separate designs were formed, but designs were for a mobile application aiming to bring pets and pet owners together for sportive activities. Mobile device usage has reached an indispensable level with social media applications accounting for more than thirty-five percent of total mobile application usage in 2024 (Statista, 2025). Nearly half of the total screen time spent on social media apps in a day (Coyne et al., 2023).

In 2018, approximately 67% of the U.S. households owned a pet, according to the American Veterinary Medical Association. Following the COVID-19 in 2020, households' pet-owning proportion in the United States rose substantially, reaching the greatest level in history, with 70% (Kretzler et al., 2022).

People tend to ignore other people that they do not know in public. But researches shows that pets can trigger social interactions (Wood et al, 2015). Pet owners are more prone to meet people in their neighbourhood than people do not have pets (Wood et al, 2015).

Considering the reasons above, a social media application focused on pet owners was chosen, to examine the effect of Generative AI on brand identity.

To generate a design through GenAI, ChatGPT and DALL-E were used. The human designer received the same brief as the GenAI. These briefs were included the main characteristics of the brand, (for example a hedonic brand, a premium brand, a symmetrical logo etc.). Brand name, brand slogan and other design decisions were left to the designer and Gen AI.

In the first part, designs created by GenAI shown to the participants without saying it is a GenAI creation, and the feelings and effects it created was asked to the participants. In the second part of the questionnaire, same process was repeated with exposing designer-produced designs.

The questionnaire ends with the third part, which consists demographical questions.

4.1 Sample Characteristics

Demographic analyses revealed that 66% of the participants were under 35. While seniors are conducting 6.5% of the sample, middle age group makes-up nearly 30% of the sample. Women comprised nearly 45% of the group.

Participants' educational background was concentrated in undergraduate studies. 53% of the participants are graduated from undergraduate courses or still studying at. Master’s degree and high school level participants are consisting 15% and 21% of the sample, respectively. 63% worked private sector employee, while 19.8% are students. 150 participants stated their monthly income is above 50000 TL. In the study, educational level indicates the highest level completed or currently pursued.

Average mobile application using time is concentrated between 1-4 hours, which comprise 60% (1-2 hours 30%, 2-4 hours 30%) of all participants. For internet using time, more than 5 hours users are consisting 35% while 3-5 hours consist 37%. Those using internet between 1-3 hours constituted 21% of the sample.

78.7% of the participants stated that they never used an application similar to ones promoted in the questionnaire.

5. Results

5.1 Factor Analysis

Exploratory Factor Analysis was conducted on questionnaire items, principal components method with Varimax rotation applied and coefficients under 0.50 were suppressed.

Due to the first EFA made for design characteristics constructs, the requirement of composing informativeness and reliability constructs has been revealed. This is consistent with the prior findings of Ye et al. (2024), in which the amount of beneficial information in an advertisement increases its perceived credibility. Informativeness and reliability were combined post-hoc, as EFA also showed loadings were acceptable when these two factors were merged. Also, hypotheses H4 and H6 combined together as H4 as below.

H4. Ad credibility of the advertisement affects the purchasing intention positively.

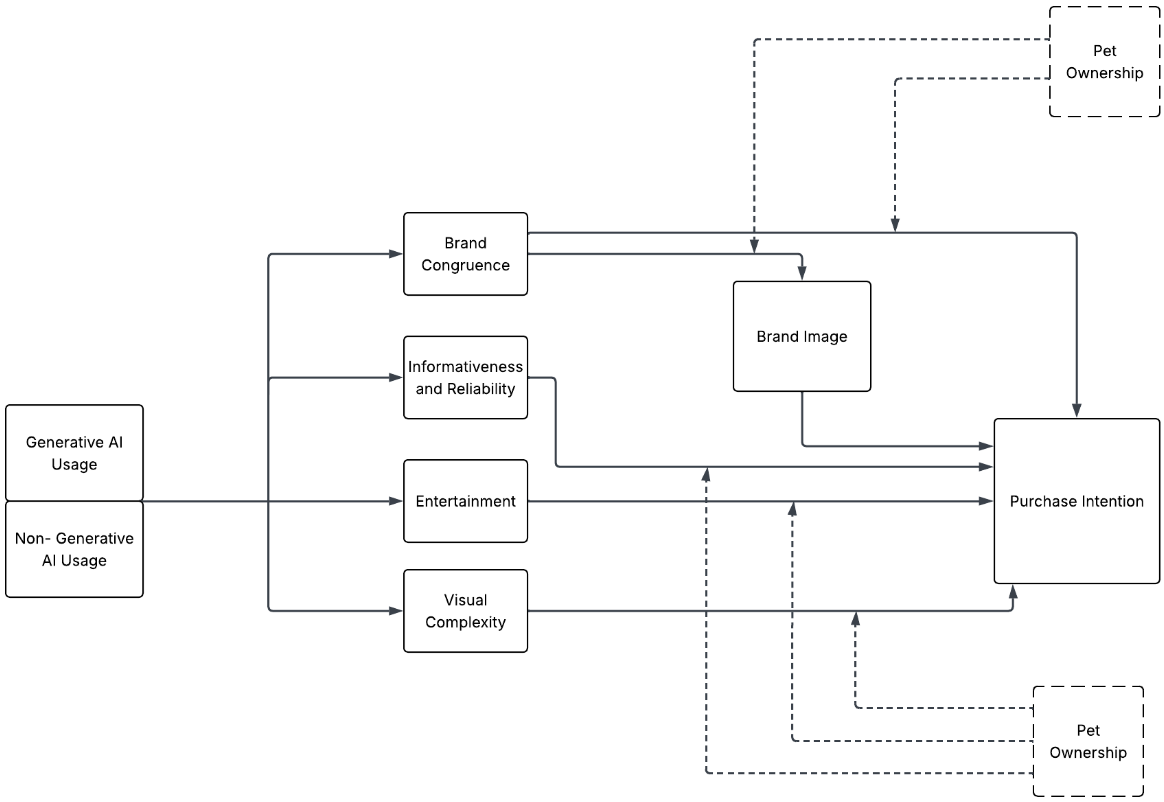

Figure 1: Revised Research Model

Factors are divided into three, before analyses. First construct included the design factors (visual complexity, informativeness, entertainment and reliability). Second construct included brand characteristics items (brand image, brand attitude and consumer-brand congruence). Purchase intention held separate from other factors as a third individual group. Subsequent to EFA, reliability analyses were made to find out if the items are coherent and stabile.

For design construct, Kaiser-Meyer Olkin (KMO) calculated as 0.937 for AI-Generated and 0.940 for designer produced, showed the data is acceptable for the factor analysis, while Cronbach's α values being at least 0.832 and 0.892 respectively showed that constructs are reliable. For AI-Generated 77.180% of the total variance explained by the extracted factors and for designer produced design 82.357% of the total variance explained by the extracted factors.

For brand constructs, KMO calculated as 0.938 for AI-Generated and 0.947 for designer produced, and all the Cronbach's α values being at least 0.849 and 0.873 respectively. For AI-Generated design 79.748% of the total variance explained by the extracted factors and it is 83.913% for designer produced design.

KMO calculated as 0.723 for purchase intention for AI-Generated designs and 0.749 for designer produced designs; while Cronbach's α values found 0.875 and 0.915 respectively. While 79.729% of total variance explained in AI-Generated model, it is 85.337% for designer produced model.

Bartlett's Test of Sphericity Significance Level found $p < 0.001$ for both models indicated that the variables are significantly correlated, for all three constructs.

Model for AI-Generated found acceptable in the Confirmatory Factor Analysis (CFA). After the marker variable added, a slight decline occured on indices while factor loading decreased by 0.109, and the marker accounted for 25.8% of the total variance, which is slightly over 25.0%.

Table 1. CFA Model Fit for AI-Generated Design and Common Method Variance Analysis with Marker Method

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA [90% CI]	NFI
AI-Generated	643.778	278	2.316	0.937	0.927	0.074 [0.067, 0.082]	0.895
**Marker-Added*	719.877	279	2.580	0.925	0.905	0.081 [0.074, 0.089]	0.884

For designer-produced condition, model found acceptable in the CFA as well. After the marker variable added, a slight decline occurred on indices while factor loading decreased by 0.023, and the marker accounted for 4.2% of the total variance, which is well below the 25.0% threshold.

Table 2. CFA Model Fit for Designer-Produced Design and Common Method Variance Analysis with Marker Method

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA [90% CI]	NFI
Designer-Produced	722.897	278	2.600	0.935	0.924	0.084 [0.077, 0.092]	0.899
(Marker added)	734.863	279	2.643	0.933	0.916	0.085 [0.078, 0.093]	0.884

Notably, none of the factor loading became non-significant after controlling for the marker variable, demonstrating that common method variance is not a serious threat to invalidate the model, although added to the limitations since accounted percentage of total variance and factor loading change are slightly over the acceptable range (Full factor loadings are reported in Appendix B).

Since both designs were evaluated using same population, a combined model was created in order to apply the invariance analysis (see Appendix B for factor loadings and model fit). In the measurement invariance analysis, despite the $\Delta\chi^2$ for scalar step being significant with $p = 0.002$, with $\Delta CFI \leq 0.001$ and $\Delta RMSEA \leq 0.001$ values, both metric and scalar invariances are valid for the complete model which includes both AI-Generated and Designer produced conditions.

Table 3. Measurement Invariance Analysis

Model	χ^2	df	CFI	RMSEA	$\Delta\chi^2$
Configural	2874.329	1199	0.874	0.079	-
Metric	2889.738	1218	0.875	0.078	15.409, p = 0.696
Scalar	2912.755	1225	0.874	0.078	23.017, p = 0.002

Mediation analyses were applied on brand image -> purchase intention, brand congruence –> brand and brand congruence –> purchase intention. Due to the results, partial mediation of brand image is valid for both AI and designer conditions.

Table 4. Mediation Analysis Results

	AI-Generated			Designer Produced		
Path	**β**	**95% BC Bootstrap CI**	**p**	**β**	**95% BC Bootstrap CI**	**p**
Congruence → Brand Image	0.869	[0.801, 0.921]	<0.001	0.896	[0.843, 0.940]	<0.001
Brand Image → Purchase Intention	0.342	[0.058, 0.599]	0.017	0.300	[0.046, 0.592]	0.021
Congruence → Purchase Intention (direct)	0.657	[0.409, 0.914]	<0.001	0.654	[0.346, 0.897]	<0.001
Indirect effect	0.298	[0.053, 0.529]	0.015	0.269	[0.047, 0.552]	0.019
Total effect	0.954	[0.913, 0.991]	<0.001	0.922	[0.865, 0.962]	0.001

5.2 Regression Analyses

Table 5. Regression Analysis Results for AI-Generated Design

Hypothesis	Independent Variable	Dependent Variable	Standardized β	t	p	R²	Adj. R²	F	df	Sig.	VIF
H1	Brand Image	Purchase Intention	0.799	21.333	< 0.001	0.638	0.637	455.111	258	< 0.001	1.000
H2	Brand Congruence	Brand Image	0.787	20.480	< 0.001	0.619	0.618	419.433	258	< 0.001	1.000
H2	Brand Congruence	Purchase Intention	0.859	26.862	< 0.001	0.737	0.736	721.547	257	< 0.001	1.000
H3	Visual Complexity	Purchase Intention	0.014	0.249	0.804	0.592	0.587	123.617	256	< 0.001	1.942
H4	Credibility		0.518	7.665	< 0.001						2.863
H5	Entertainment		0.285	4.431	< 0.001						2.595

Table 6. Regression Analysis Results for Designer-Produced Design

Hypothesis	Independent Variable	Dependent Variable	Standardized β	t	p	R²	Adj. R²	F	df	Sig.	VIF
H1	Brand Image	Purchase Intention	0.809	22.107	< 0.001	0.654	0.653	488.722	258	< 0.001	1.000
H2	Brand Congruence	Brand Image	0.839	24.722	< 0.001	0.703	0.702	611.171	258	< 0.001	1.000
H2	Brand Congruence	Purchase Intention	0.868	28.012	< 0.001	0.753	0.752	784.685	258	< 0.001	1.000

<table>
<tr><th>Hypothesis</th><th>Independent Variable</th><th>Dependent Variable</th><th>Standardized β</th><th>t</th><th>p</th><th>R²</th><th>Adj. R²</th><th>F</th><th>df</th><th>Sig.</th><th>VIF</th></tr>
<tr><td>H3</td><td>Visual Complexity</td><td rowspan="3">Purchase Intention</td><td>−0.081</td><td>−1.523</td><td>0.129</td><td rowspan="3">0.692</td><td rowspan="3">0.688</td><td rowspan="3">192.120</td><td rowspan="3">257</td><td rowspan="3">< 0.001</td><td>2.376</td></tr>
<tr><td>H4</td><td>Credibility</td><td>0.487</td><td>7.681</td><td>< 0.001</td><td>3.352</td></tr>
<tr><td>H5</td><td>Entertainment</td><td>0.452</td><td>7.392</td><td>< 0.001</td><td>3.110</td></tr>
</table>

H1 was tested for each model with calculating $p < 0.001$. In the model for AI-Generated designs, B = 0.805 (95% CI [0.731, 0.879]), $\beta = 0.799$, Adj.$R^2 = 0.637$, while B = 0.905 (95% CI [0.824, 0.986]), $\beta = 0.809$, Adj.$R^2 = 0.653$ for designer produced design, showing brand image is a significant predictor of purchase intention for both designs.

For H2, brand congruence was selected as the independent variable, while brand image and purchase intention were selected as the dependent variables, in separate runs. For AI-Generated design's brand congruence - brand image pair, B = 0.735 (95% CI [0.664, 0.806]) $\beta = 0.787$, Adj.$R^2 = 0.619$, $p < 0.001$.

For AI-Generated design's brand congruence – purchase intention pair, B = 0.808 (95% CI [0.749, 0.867]), $\beta = 0.859$, Adj.$R^2 = 0.736$, $p < 0.001$.

When the regression analysis done for the designer-produced design, brand congruence – brand image pair, B = 0.734 (95% CI [0.675, 0.793]), $\beta = 0.839$, Adj.$R^2 = 0.653$, $p < 0.001$. For brand - purchase intention pair, B = 0.849 (95% CI [0.789, 0.909]), $\beta = 0.868$; Adj.$R^2 = 0.752$, $p <0.001$. Results showed that H2 is valid and meaningful for both designs.

Another regression analysis conducted in order to testing H3, H4, H5 together, to examine the design constructs and their effects together. Results showed that testing credibility construct of AI-generated design revealed B = 0.537 (95% CI [0.399, 0.674]), $\beta= 0.518$. For the designer produced model, B = 0.532 (95% CI [0.396, 0.669]), $\beta = 0.487$. On both models, $p < 0.001$. For entertainment construct, $p < 0.001$ for both models while B = 0.323 (95% CI [0.180, 0.467]), $\beta = 0.285$ and B = 0.506 (95% CI [0.371, 0.640]), $\beta = 0.452$, for AI-Generated and designer produced designs, respectively. Both credibility and entertainment constructs found significant predictors of purchase intention.

For visual complexity construct of AI-Generated design, B = 0.015 (95% CI [-0.105, 0.136]), $\beta = 0.014$ and $p = 0.804$. For the designer produced model, B = -0.092 (95% CI [-0.210, 0.027]), $\beta = -0.081$, $p = 0.129$. Analysis showed that visual complexity is not a significant predictor of purchase intention for both designs.

All VIF < 3.3, except for the 'credibility factor of designer-produced design', with a VIF = 3.352. All the tolerance values were above 0.20. No collinearity detected between variables of hypotheses.

5.3 Paired-Sample t-Test

Between designs statistically significant difference detected only in visual complexity (ΔMean (AI-Ds) = -0.205 (95% CI [-0.322, -0.087]), $p < 0.001$, Cohen's d = -0.214 (95% CI [-0.338, -0.090]) and purchase intention (ΔMean (AI-Ds) = -0.119, (95% CI [-0.213, -0.025]), $p = 0.014$, Cohen's d = -0.158 (95% CI [-0.282, -0.032])) constructs. However, both of them have small effect sizes, and may negligible.

5.4 Independent Sample t-Test

Significant differences were detected in, brand attitude (ΔMean = 0.335 (95% CI [0.087, 0.583]), Cohen's d = 0.343 (95% CI [0.088, 0.596])) and purchase intention (ΔMean = 0.340 (95% CI [0.058, 0.621]), Cohen's d= 0.307 (95% CI [0.052, 0.562])) for AI-Generated design; brand congruence (ΔMean = 0.388 (95% CI [0.077, 0.699]), Cohen's d= 0.316 (95% CI [0.062, 0.569])), brand attitude (ΔMean = 0.353 (95% CI [0.074, 0.633]), Cohen's d= 0.320 (95% CI [0.066, 0.574])) and purchase intention (ΔMean = 0.348 (95% CI [0.050, 0.645]), Cohen's d= 0.286 (95% CI [0.032, 0.541])) in designer-produced design, with measuring $p < 0.05$. The "d" values indicate small effect sizes for all constructs.

To conduct the independent t-test by gender, one participant who gave the answer "I don't want to answer" to the gender question was excluded. Results showed that no significant difference was found across gender groups (all $p > 0.05$).

5.5 One-Way ANOVA

As all variables had $p > 0.05$ from Levene's test for homogeneity, variances were assumed as homogeneous.

For credibility, the master's group had significantly lower scores compared to the high school group (M_Diff = -0.898 (95% CI [-1.580, -0.217]), p = 0.003), when they encountered AI-Generated designs, same pattern applied to master's group for designer-produced design (M_Diff = -0.926 (95% CI [-1.626, -0.227]), p = 0.003).

For consumer-brand congruence, exposed to AI-Generated designs, the high school group scored higher than the bachelor's group (M_Diff = 0.578, (95% CI [0.01, 1.146]), p = 0.044), and to the master's group (M_Diff = 1.159, (95% CI [0.424, 1.895]), $p < 0.001$). Master's group obtained lower scores compared to the associate's group (M_Diff = -1.054 (95% CI [-2.032, -0.075]), p = 0.027). For designer produced images, bachelor's group obtained higher scores compared to master's group (M_Diff = 0.740, (95% CI [0.078, 1.402]), p = 0.019) and master's group has lower scores against high school group (M_Diff = -1.205, (95% CI [-1.970, -0.440]), $p < 0.001$) and against the associate's group (M_Diff =-1.058, (95% CI [-2.066, -0.050]), p = 0.034). Based on the analysis done, master's group is developing congruence harder than other educational groups.

The master's group scored lower in brand image compared to the high school group (M_Diff = -1.127, (95% CI [-1.809, -0.444]), $p < 0.001$) and compared to the associate's group (M_Diff = -1.025, (95% CI [-1.918, -0.132]), p = 0.014). High school group scored higher than the bachelor's group (M_Diff = 0.558, (95% CI [0.032, 1.085]), p = 0.031), upon exposure of AI-Generated designs. When exposed to designer created designs, the approaches did not differ.

For purchase intention, the master's group scored lower compared to the high school group (M_Diff = -1.018, (95% CI [-1.718, -0.318]), $p < 0.001$) and against the associate's group (M_Diff = -1.159, (95% CI [-2.088, -0.231]), p = 0.005), for AI-Generated designs. When exposed to designer created designs, the approaches did not differ.

6. Discussion

This study examined AI's effect on consumer behaviour and preferences, across brand characteristics. All hypotheses, except H3, were supported by the experiment although no strong advantage of using AI tools was found compared to conventional techniques. Results supported that brand image is a strong predictor of purchase intention. Results showed that consumer-brand congruence is a factor which boosts brand image, meanwhile it is enhances purchase intention of the consumers. Brand image partially mediated the effect of brand congruence on purchase intention, for both AI and designer conditions. While testing all design elements, entertainment, informativeness and reliability found as another important aspects on consumer's purchasing behaviour, as design characteristics while visual complexity did not.

One-Way ANOVA test underline the significant effect of educational status, both for AI-Generated and designer produced designs.

Specifically, master's group have significantly underscored compared to high school group in credibility, brand image, consumer-brand congruence and purchase intention, while associate's group also had higher scores than master's degree group in more than one constructs. These results show that master's degree holders and students are more sceptical and selective when introducing a new product, compared to specifically lower educational level participants. On the other hand, no significant difference was found between age groups for both approaches.

7. Limitations and Future Research

The study did not counterbalance the order of exposure, instead introduced the questionnaire in single flow. Future studies should obtain a counterbalanced exposure, to understand if order effect affects the results significantly. The study did not conduct a manipulation check. Future studies should conduct a manipulation check to understand if consumers can distinguish differences between AI-Generated and designer produced designs.

Common method bias was assessed using a single-item marker; despite loadings decreased none of them turned non-significant. However, as the marker technique does not fully address the bias concern, future studies should consider preventive approaches more robustly through multi-method design or temporal separation.

Since participants in this study were recruited only from Türkiye, generalizing the findings to other cultures may be limited. The snowball sampling method which has been used to reach the participants in the experiment may cause a less diverse sample in terms of demographic and attitudinal characteristics. Future research should apply a cross-national and probability-based sampling approach in data collection.

Information of whether the design is generated by AI or produced by a designer is not disclosed to the participants. The results may vary in a context where AI usage is disclosed to the participants, correlated to the detail level of disclosure and the pertinence (Pierre et al., 2026), which should be taken into account by the future studies.

8. Conclusion

This study underlines that there is no significant difference practically between AI-Generated and designer produced designs from consumer sight. Although it is an interesting result from consumer's sight; regardless of there is no significant positive effect of GenAI usage found, no remarkable drawbacks detected neither. Since the usage of artificial intelligence is supplying savings on time and effort wise, more common acceptance of using artificial intelligence on branding may need to be considered.

On the other hand, educational level is a significant variable for brand image, purchase intention, brand congruence and credibility in common for both cases. In spite of it, age groups and gender did not show any remarkable differences.

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Appendix A. Scale Items

Table A1. Scale Items

Construct	Scale Item	Source
Brand Image	This service seems attractive.	Ali et al., (2025)
	This service seems different from other traditional services.	Ali et al., (2025)
	This brand has a good history.	Kumar et al. (2024)
	This brand is reliable for performance.	Kumar et al. (2024)
Brand Attitude	I have a pleasant idea of this brand.	Kumar et al. (2024)
	I think this brand has a good reputation.	Kumar et al. (2024)
	Using this brand's mobile application seems sensible to me.	Kumar et al. (2024)
	This brand is likable.	Brüns & Meißner (2024)
	This brand seems sympathetic to me.	Brüns & Meißner (2024)
Consumer–Brand Identification	This brand says a lot about what kind of person I am.	Graham & Wilder (2020)
	This brand's image and my self-image are similar.	Graham & Wilder (2020)
	This brand is consistent with how I see myself.	Taylor et al. (2011)
	This brand appeals to people like me.	Taylor et al. (2011)
	Using this mobile application reflects who I am.	Taylor et al. (2011)

Construct	Scale Item	Source
	Typical customers of this brand are like me.	Taylor et al. (2011)
Informativeness	This advertisement gives adequate information of this service.	Logan et al. (2012)
	This advertisement supplies pertinent information of this service.	Logan et al. (2012)
	This advertisement constitutes a useful source of information about this service.	Logan et al. (2012)
Entertainment	This advertisement is fun to watch or read.	Taylor et al. (2011)
	This advertisement is clever and amusing.	Taylor et al. (2011)
	This advertisement is entertaining to watch.	Taylor et al. (2011)
Reliability	The information given in this advertisement is credible.	Yang et al. (2013)
	This advertisement made by the brand is persuasive.	Brüns & Meißner (2024)
	This advertisement instilled a sense of trust in me.	Yang et al. (2013)
Visual Complexity	The advertisement was clear	Chen S. et al. (2025)
	The advertisement was effortless.	Chen, S. et al. (2025)
	Brand-related inferences can easily be made from the advertising image.	Chen, S. et al. (2025)
Purchase Intention	I would choose this mobile application over others.	Ali et al., (2025)
	I intend to use this brand's mobile application in the future.	Kumar et al. (2024)
	I am willing to purchase more services from this brand in the future.	Chow et al. (2025)

Appendix B. CFA Tables

Table B1. Standardized CFA Loadings for AI-Generated and Designer-Produced Designs

Factor	Item	Standardized Loading	Item	Standardized Loading
Entertainment	ai_entert1	0.761	des_entert1	0.819
Entertainment	ai_entert2	0.872	des_entert2	0.880
Entertainment	ai_entert3	0.791	des_entert3	0.863
Visual Complexity	ai_vcompl1	0.861	des_vcompl1	0.906
Visual Complexity	ai_vcompl2	0.858	des_vcompl2	0.869
Visual Complexity	ai_vcompl3	0.734	des_vcompl3	0.843
Brand Image	ai_brimage1	0.844	des_brimage1	0.857
Brand Image	ai_brimage2	0.884	des_brimage2	0.887
Brand Image	ai_brimage3	0.701	des_brimage3	0.786
Congruence	ai_congr1	0.867	des_congr1	0.911

Factor	Item	Standardized Loading	Item	Standardized Loading
Congruence	ai_congr2	0.906	des_congr2	0.921
Congruence	ai_congr3	0.878	des_congr3	0.903
Congruence	ai_congr4	0.845	des_congr4	0.885
Congruence	ai_congr5	0.868	des_congr5	0.895
Congruence	ai_congr6	0.841	des_congr6	0.892
Credibility	ai_inform2	0.830	des_inform2	0.864
Credibility	ai_inform3	0.807	des_inform3	0.860
Credibility	ai_reliab1	0.825	des_reliab1	0.887
Credibility	ai_reliab2	0.874	des_reliab2	0.887
Credibility	ai_reliab3	0.853	des_reliab3	0.876
Brand Attitude	ai_attitude1	0.806	des_attitude1	0.906
Brand Attitude	ai_attitude2	0.849	des_attitude2	0.894
Brand Attitude	ai_attitude3	0.865	des_attitude3	0.858
Purchase Intention	ai_purchase1	0.828	des_purchase1	0.909
Purchase Intention	ai_purchase2	0.812	des_purchase2	0.861
Purchase Intention	ai_purchase3	0.866	des_purchase3	0.877

Table B2. Standardized CFA Loadings for Combined Model

Factor	AI Item	Standardized Loadings (AI)	Designer Item	Standardized Loadings (Designer)
Entertainment	ai_entert1	0.777	des_entert1	0.821
Entertainment	ai_entert2	0.867	des_entert2	0.882
Entertainment	ai_entert3	0.787	des_entert3	0.859
Visual Complexity	ai_vcompl1	0.853	des_vcompl1	0.904
Visual Complexity	ai_vcompl2	0.858	des_vcompl2	0.867
Visual Complexity	ai_vcompl3	0.718	des_vcompl3	0.839
Brand Image	ai_brimage1	0.831	des_brimage1	0.852
Brand Image	ai_brimage2	0.890	des_brimage2	0.889
Brand Image	ai_brimage3	0.677	des_brimage3	0.784
Congruence	ai_congr1	0.858	des_congr1	0.910
Congruence	ai_congr2	0.901	des_congr2	0.920
Congruence	ai_congr3	0.871	des_congr3	0.901
Congruence	ai_congr4	0.826	des_congr4	0.883
Congruence	ai_congr5	0.850	des_congr5	0.891
Congruence	ai_congr6	0.829	des_congr6	0.887

Factor	AI Item	Standardized Loadings (AI)	Designer Item	Standardized Loadings (Designer)
Credibility	ai_inform2	0.821	des_inform2	0.857
Credibility	ai_inform3	0.800	des_inform3	0.854
Credibility	ai_reliab1	0.823	des_reliab1	0.883
Credibility	ai_reliab2	0.864	des_reliab2	0.887
Credibility	ai_reliab3	0.853	des_reliab3	0.876
Brand Attitude	ai_attitude1	0.817	des_attitude1	0.908
Brand Attitude	ai_attitude2	0.869	des_attitude2	0.896
Brand Attitude	ai_attitude3	0.852	des_attitude3	0.853
Purchase Intention	ai_purchase1	0.816	des_purchase1	0.905
Purchase Intention	ai_purchase2	0.804	des_purchase2	0.862
Purchase Intention	ai_purchase3	0.864	des_purchase3	0.868

Table B3. Model Fit for Combined Model

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA [90% CI]	NFI
Combined Model	2874.329	1199	2.397	0.874	0.861	0.079 [0.075, 0.082]	0.804

Appendix C. Study Stimuli

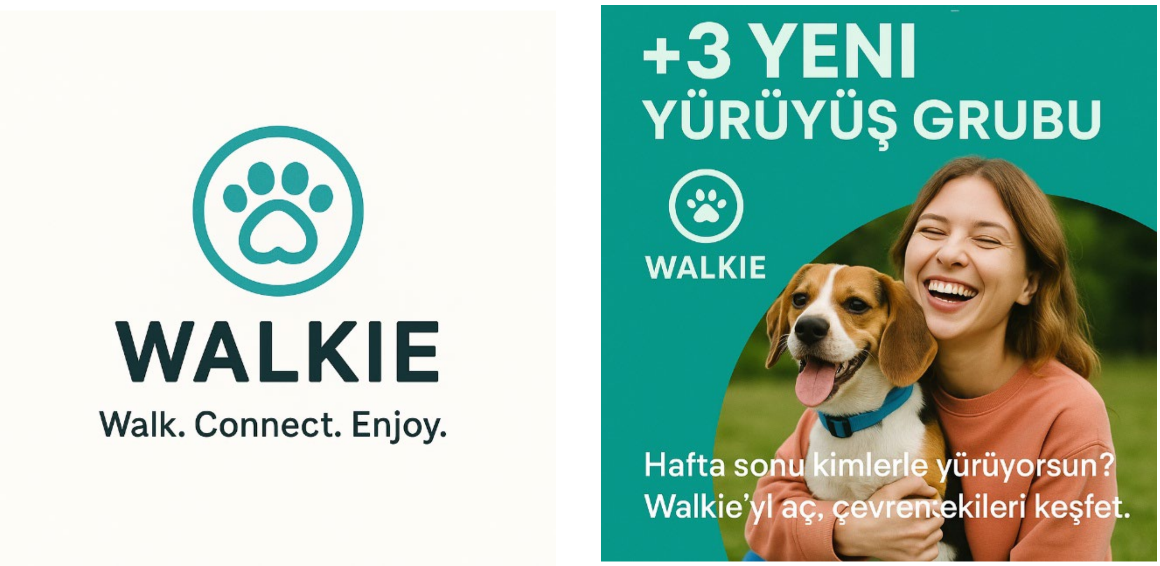

Figure C1–C2. AI-Generated Stimuli

Figure C3–C4. Designer-Produced Stimuli