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THE IMPLICATIONS OF UTILIZING AI-GENERATED IMAGERY IN ADVERTISEMENTS

Bachelor Thesis

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I have written this Bachelor Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

Table of contents

Introduction

In 2007, market research firm Yankelovich found that on average, a person is exposed to 5,000 advertisements a day. In 2024, the amount has surged twofold; with internet users being subjected to an estimated 10,000 advertisements per day. (Nadia, 2024c) The exponential growth of advertisements per day is a great indication of the efforts undertaken by teams and companies in creating digital advertisements designed to provoke higher levels of consumer engagement and purchase behavior**.** Effective advertising necessitates the selection and application of appropriate metrics, such as click-through rate, consumer perceived value, consumer purchase intent, and broader consumer behavior patterns (Reena & Udita, 2020)**.** The efficacy of ads providing favorable returns for companies highlights the importance of the creative process involved in the production and the allocation of resources. The resources generally used for producing ads could be diverted to alternative necessities for a company, provided there is a powerful enough substitute.

Artificial Intelligence (AI), a tool designed to capture human intelligence and replicate it artificially, has demonstrably surpassed human capacity in numerous tasks previously considered to be exclusive to the human labor domain. While this technological progress offers countless benefits, it also raises concerns about AI's potential to become a threat. With the fast-paced development of AI, most of the manual labor sector jobs have been overtaken by machinery. Seemingly, humans are still naive to the advancements of AI and underestimate the improvements that may arise in its potential for creative tasks. The concept that AI lacks creativity due to its inability to feel emotions has been a longstanding argument against its takeover in artistic fields. (*Artificial Intelligence Yesterday, Today and Tomorrow*, 2019; Boden, 1998)

However, the recent launch of projects like OpenAI's Google Gemini, tasked with generating historical imagery, provides strong evidence for the potential of AI in creative fields. Despite the slight inaccuracies like the Nazis and America’s founding fathers as people of color, just to fit the standards of inclusivity today, it demonstrates that AI is not far from improving with necessary modification toward more realistic image creation. These projects showcase AI's significant strides and its potential to become a powerful creative tool. (Bonk, 2024) Generative AI is a subset of Artificial Intelligence technology that can create different types of content such as images, poems, music. The rapid development of Generative AI has narrowed the gap between real and artificial imagery. (Lawton, 2024) However, technology still produces images that deviate from reality, often containing imperfections and/or defects

(*CIFAKE: Image Classification and Explainable Identification of AI-Generated Synthetic Images*, 2024).

This rationale sets a basis for investigating whether the perceived value of realistic image advertisements is different compared to AI-generated images. By determining whether the perceived value remains the same, the question can be asked: Is it possible to replace all the resources that go into the creative process of creating a background image for an advertisement with a simple AI text-to-image prompt? A text-to-image prompt refers to a specific type of instruction used in software that allows the creation of original visual art based on a textual description (Dehouche & Dehouche, 2023).

Building upon prior research that has explored the impact of AI imagery on consumer engagement, consumer reaction to manipulated advertising, and the creation of frameworks for understanding responses to such imagery, this thesis stands out with a specific aim. (Matthews et al., 2023; Campbell et al., 2022; Du et al., 1970; Li, 2019) Existing studies haven't directly investigated the influence of AI-generated imagery on Consumer Perceived Value (CPV) in advertisements.

The aim of this thesis is to find out the possibility of replacing real photos with images generated by AI for the background pictures of advertisements. The author will create an experiment using Consumer Perceived Value as a metric to compare AI-imagery with real images. If, in the author's experiment, by comparing images through conducting surveys, AI-generated backgrounds are perceived of higher value to the consumer than real images, then companies can investigate consolidating the resources that go into creating the real images for display advertising and replace the process with AI image generation. The results of this experiment provide valuable insights for a couple of key audiences. The marketing and advertisement departments in companies can gain insights into utilizing alternative creativity (AI-generated imagery) for content creation. Business owners and executives could also rethink resource allocation and advertising budgets. Lastly, the experiment’s results offer valuable data to technology developers and researchers, as AI-developers can take the results as feedback and create higher-quality and more effective tools for image generation, ultimately contributing to the advancement of the technology itself. This experiment will examine how AI-generated backgrounds, compared to traditional/real photography, affect a consumer's perception of a product's value.

The author has set the following tasks in order to ensure that the aim of the thesis is reached:

- Define “Advertisement,” “Artificial Intelligence generated,” “Generative AI,” and “Display Ads.”
- Explain the importance of imagery and backgrounds in an advertisement.
- Discuss the shortcomings of generative AI.
- Find and select real images and thereafter create AI-generated imagery for comparison purposes.
- Distribute surveys and gather data for the analysis phase of the experiment.
- Generalize the data and discuss the findings.

The theoretical part will consist of an analysis of definitions and the research of previous studies where AI-generated imagery was scaled. The author sets a research question to start researching in the empirics. In the second part of the thesis, the empirical part is presented. The empirical analysis consists of the data and methodology, the analysis of results, and the discussion of findings. The author produces images to use in the experimentation and lastly, analyzes the collected data and findings based on the research. The findings imply that the aim of this research has been reached and proposes future research possibilities. Additionally, the conclusion provides a concise overview of the research. At the end of the thesis, the author thanks their supervisor, Tanel Mehine, as well as other persons who aided with the experiment as well as counseling and giving a sense of direction in this research.

Keywords: AI-generated imagery, Advertisement, Visual Imagery, Consumer Perceived Value.

1. The Conceptual Framework of Advertisements

1.1. Visual Elements in Advertising

According to Statista (2023) the global expenditure for digital ad spend hit $600 billion in 2023 and is expected to reach $1,088 billion in 2024. Therefore, it is safe to say that it is not short of being one of the biggest advertising markets. An advertisement has many elements, and combining everything gives it the power to persuade to purchase. The different components of an advertisement include a slogan, the logo, the offer, an image, etc. (Wilson, 2020). The author will focus on the image in an advertisement, and more specifically in a digital advertisement. A visual ad can be categorized into many different categories, dynamic or static advertisement, traditional or digital, contextual or behavioral, etc. (Auschaitrakul & Mukherjee, 2017; Goldfarb and Tucker, 2011) Notably, the distinction between dynamic and static ads, while not strictly contradictory to one another, offers a valuable categorization framework. Dynamic advertisements leverage user data to personalize content, allowing them to adapt to individual viewers. In contrast, static advertisements present a consistent message to all viewers, leaving the image/message unchanged. (Auschaitrakul & Mukherjee, 2017) Senders (1997) defined it as "the one involves the attracting of attention; the other the paying of attention." The author would define the very essence of a dynamic and static ad in building upon Senders' (1997) foundational concept - the dynamic ad is the ad that attracts attention, and the static ad is the one to pay attention to. The distinction between contextual and behavioral advertising lies in the border of privacy. Contextual advertising when compared to behavioral is less privacy-invasive, as behavioral advertising develops personalized ads based on consumer behavior and personal data. (Bleier, 2021)

Visual advertising incorporates formats delivered on physical mediums like different ads on newspapers. However, the key distinction lies in the differentiation between traditional advertising and its digital equivalent. Traditional advertising refers to the old-school advertisements such as print ads, billboards, television ads, mailing ads, etc. (Eisend, 2018) Digitalization in advertising has led companies to develop better ways to collect insights on user interaction with their ads. This has resulted in a better understanding of customer behavior, enabling companies to create more effective advertising campaigns (Eisend, 2018). There is a wide array of different types of digital advertisements but display ads will be of concern in this thesis (Figure 1). Visual advertising encompasses a diverse range of formats, as depicted in the graph.

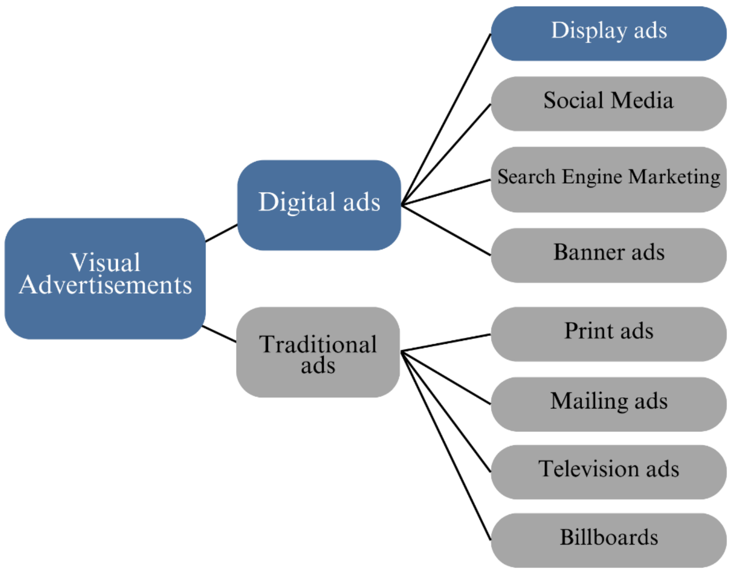

Figure 1: Categorization of Visual Advertisements

Note: The blue color represents the direction this thesis is going in.

Source: Compiled by the author based on Auschaitrakul & Mukherjee (2017); Goodlow (2019); Purusothaman & Rajalakshm, (2017); Eisend, (2018) Display ads are a versatile advertising format that appear on social network sites and other online platforms. They come in a wide range of visual styles, incorporating elements like color, texture, shape, and background design (Mukherjee & Auschaitrakul, 2017). Display ad success is primarily evaluated based on the incoming traffic to the advertiser's website. Conversion rates or ad clicks are not the sole metrics for success in this context (Triblio, 2024). There are many different roles of a visual image presented in an advertisement. The image in an advertisement is a choice of the style of delivery. “The function of a trope is to present a proposition in a fresh way so that the audience thinks about a familiar issue from an unexpected perspective.” (Scott, 1992, p. 254). Scott (1992) specified in his research that the primary function of a visual representation is to forge new links in the consumer's mind to different topics that could induce purchase trends. Images can be used in advertisements to plant a seed in the consumer's mind and influence them to achieve the desired outcome, which would be an increase in purchase intention (Zhang et al., 2020).

Different types of visual imagery can have different effects on people’s inclination to buy. In a study by Muehling, Sprott, and Sultan (2014), empirical data on “nostalgia-themed advertisements” was examined, and the outcome was that childhood brand exposure through imagery and emotional connections with associated brands did have a positive effect on purchase intent as opposed to non-nostalgic imagery. (Muehling et al., 2014) This effect may be attributed to the perception of nostalgic items as priceless, leading to a higher inclination to buy in consumers.

As highlighted in the research by Khong (2010), the consumer's attitude to an image in an advertisement can be categorized into affective components, which are influenced by feelings, and cognitive components, which are affected by the judgment. “For example, consumers’ attitude toward the advertisement is favorable’ when they read/click/play it or ‘unfavorable’ when they ignore it… favorable attitudes will have a positive impact on purchase decision.” (Khong, 2010, p. 116). Display ads have specific components that contribute to its structure, such as “a single file that typically have a background graphic or color, a clear business logo, and a call-to-action.” (Triblio, 2024). Beyond these core components, display ads can incorporate a variety of elements such as promotional messages, social proof indicators, or urgency signals to surge or enhance purchase intent. (Devlin et al., 2007) Figure 2 depicts a schematic representation of a display advertisement's structure.

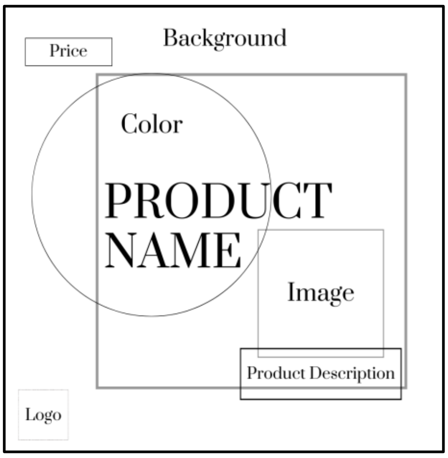

Figure 2: A display ad's structure

Source: Compiled by the author based on Triblio (2024); Wilson (2020).

A very important component of an advertisement is the color. Studies have shown that integrating color into an ad has shown the effect of having a higher consumer engagement rate. (Lohse & Rosen, 2001; Lindström, 2011) Researcher Petiet (2012) found a significant effect of color contrast on product attention. Products with high-contrast backgrounds were more likely to attract attention compared to those with lower contrast. (Petiet, 2012; Wu et al., 2016)

The background is one of the main components of an image. (Scott, 1992) According to an experiment done by De Vries et al. (2013), background luminance can impact search performance by either distracting or increasing search time. The experiment showed that backgrounds with lower luminance cause higher distraction rates in viewers than backgrounds with higher luminance. (De Vries et al., 2013; De Vries et al., 2013b) If background saturation analysis is considered, then in regular circumstances, spotting a high-saturated object among other less saturated ones is easier. However, Rosenholtz, Nagy, and Bell (2004) found that changing the background color can have a contradictory effect. This means that sometimes, it is easier to locate a less-saturated object on a high-contrast, high-saturation background.

Lewandowska and Olejnik-Krugly (2021) conducted an eye-tracking experiment to investigate user preferences for user-friendly and readable color combinations. While the study aimed to assess the impact of background color on users' unconscious first impressions, the results yielded an unanticipated outcome. The research found that background color, in some cases, did not significantly influence the user's perception of the visual message, even when the intention was to grab and hold their attention. However, building on the findings of color contrast, Turatto and Galfano (2000) investigated the combined influence of color, shape, and effect (possibly visual effects) on attention and purchase behavior. Their research suggests that these elements, when strategically combined, can indeed attract human attention, and potentially lead to higher purchase rates (Chandon and Wansink, 2002; Wu et al., 2016). Furthermore, the study by Wolfe et al. (2002) found that when the background of an image was heterogeneous, the search volume increased significantly without impacting the search efficiency. These previous studies form a base for the empirical part of the author's research due to the different results and interpretations of the impact of background imagery on consumer perception. The interpretations of a background are what forms the value in the viewer's mind. The concept of "value" is a key element in marketing. Experts in marketing are tasked with creating strategies that align with what consumers deem valuable. This focus on consumer perceived value (CPV) is crucial for driving brand loyalty and cultivating long-term success (Flint et al., 1997 & Woodruff, 1997). A high CPV is essential for advertising effectiveness, as it translates to a greater likelihood of purchase.

Numerous models in marketing address the concept of consumer perceived value. CPV consistently emerges as a crucial outcome within these general models of consumer behavior (Babin et al., 1994; Demirgüneş, 2015; Chacour & Ulaga, 2001). The different explanations and definitions for the term "Consumer Perceived Value" are discussed below.

Table 1

Definitions of the term "Consumer Perceived Value." (CPV)

Source:	Definition:
Grewal et. al. (1988)	Perceived value can be measured through transaction and acquisition values.
Grönroos (1997)	CPV can be measured and assessed through cognitive and emotional function.
Sweeney and Soutar (2001)	CPV can be categorized into compounds of emotional, social, quality, and price.
Arnold and Reynolds (2003)	A prominent driver is aesthetics in enhancing consumer perceived value.
Gounaris, Tzempelikos and Chatzipanagiotouslim (2007)	Six key factors shape CPV: 1) Product value, 2) Procedural value, 3) Personnel value, 4) Emotional value, 5) Social value, 6) Perceived Sacrifice.

Source: Compiled by the author based on findings of Gounaris, Tzempelikos and Chatzipanagiotouslim, (2007); Arnold and Reynolds (2003); Sweeney, and Soutar (2001); Grewal et. al., (1988); Grönroos (1997).

The definitions by Sweeney and Soutar (2001) and Gounaris et al. (2007) both view consumer perceived value (CPV) as a phenomenon influenced by a combination of various factors. Sweeney and Soutar (2001) highlight specific factors like emotions, social perception, product quality, and price, while Gounaris et al. (2007) offer a more extensive list, including elements like product value, emotional value, and social value. Furthermore, authors Arnold and Reynolds (2003) highlight the consideration of aesthetics as an important driver in enhancing the perceived value of consumers. While the other authors focused more on thoughts and concepts, Arnold, and Reynolds (2003) focused on visual appeal. The previous research on background color affecting purchase intention in consumers emphasizes the importance of visual appeal. Although Grönroos (1997) emphasizes cognitive features in the term, aesthetics can be considered an aspect influencing cognitive/emotional response.

In exploring the influence of AI-generated imagery on (CPV) in advertisements, this thesis will continue with the adoption of the framework centered on emotional and cognitive value creation, basing inspiration from Grönroos' (1997) perspective. Grönroos' focus on these two fundamental aspects of perceived value aligns well with the potential of AI-generated imagery to impact how consumers subconsciously both think about and feel toward advertised products.

Although the phenomenon rests on the fact that delivering consumer value is essential to the pinnacle of quality, research in developing a well-constructed value measure for CPV remained underdeveloped until recently. (Albrecht, 1992, p 7; Sweeney & Soutar, 2001) In Sweeney and Soutar's (2001) research, they highlighted the development of a scale of measurement for CPV named the PERVAL scale, which essentially “was developed to assess customers' perceptions of the value of a consumer durable good” (Sweeney & Soutar, 2001, p. 203). Other research specifies that CPV can be understood as the consumer’s general assessment and evaluation of a product’s functionalities and value proposition based on how they are perceived. (Zeithaml 1988, p. 14) In research by Lim and Ang (2013), the authors found that advertisements that incorporate metaphors into their imagery led consumers to perceive the advertised product with higher value. Zeithaml (1988) also suggests that the way CPV is interpreted might differ depending on the relative importance of quality compared to price. The quality/price trade-off has traditionally been the dominant approach to value measurement, and CPV has also been strongly linked to the quality/price relationship (Monroe, 1990). This implies that CPV is often assessed after a product is purchased. However, CPV can also be structured into “pre-purchase” and “post-purchase” stages. Authors Bolton and Drew (1991) argue Zeithaml’s (1988) assertions by pointing out the oversimplification of value assessment in CPV with the concept of quality/price trade-off. Bolton and Drew (1991) suggest going more in-depth than the quality/price ratio to bring more dimension into the concept. While Monroe (1990) emphasized price-based determinants as a key factor in value perception, Porter (1990) suggested otherwise. Providing post-purchase service leads to a higher CPV score (Porter, 1990). Porter (1990) suggests that providing post-purchase services can help enhance CPV even further. However, there is a slight distinction between perceived value and value that contributes to the satisfaction that post-purchase service provides. The distinction between the two is that perceived value can be generated by the consumer even without purchase intent. Satisfaction, on the other hand, arises from the post-purchase stage, involving the experience and use of the product itself. Many CPV assessment models rely on the satisfaction of the particular product as well. (Woodruff, 1997) However, in the more recent research by Zauner et al. (2015) and Werelds et al., (2014), the authors mentioned the need for the development of proper conceptualization of consumer perceived value as well as a stringent measurement metric. In Zauner et al. (2015) research, they determined three main metrics for CPV:

1. The Unidimensional conceptualization:

This concept focuses on the trade-off between the perceived benefits and sacrifices associated with a particular service or product. The rational behavior of a consumer wanting to maximize their own benefit.

2. The Multidimensional conceptualization

This conceptualization doesn’t base as much on the economic value as the unidimensional concept does, on the contrary it refers to the emotional value a specific product or service has on the consumer. The perceived value stems from the entire consumer journey which encompasses the experience of the purchase and the utilization/consumption of the product/service.

3. The Higher-Order conceptualization

This concept relies on the interconnectedness of the social and functional benefits for the consumer. The focus of this metric has shifted from theoretical explorations of CPV to its empirical testing and application in real-world scenarios across various constructs.

As the author will be assessing CPV in relation to AI-generated imagery used as backgrounds, then the second stage of the perceived value, the post-purchase stage, does not apply in this case, as the participants of the survey will not be purchasing these products.

It can be understood that among the many different elements in an advertisement, the background plays an important role. Researchers have found that different backgrounds have proved to have different effects on consumers, in return affecting consumer purchase intent and consumer behavior. To assess the impact of background imagery on advertising effectiveness, this research employs Consumer Perceived Value (CPV) as a key metric. The absence in the development of a specific model to measure CPV has led to different approaches such as questionnaires, interviews, surveys, experiments, etc.

1.2. The Integration of AI-generated Imagery in Advertising

Artificial Intelligence is the tool for capturing human intelligence and replicating cognitive abilities through computer science and programming. This interdisciplinary technology has advanced at immense speeds in the past decades. Artificial Intelligence has been designed to tackle a wide range of tasks traditionally considered the domain of human intelligence. These include task completion, decision-making, logical reasoning, and other cognitive abilities that were traditionally thought to be unique capabilities of humans (Huand, et al., 2019; Zhang & Lu, 2021). Many countries, recognizing its potential, are actively integrating AI into their policies, regulations, and technological development strategies.

This global race for AI leadership is driven by the belief that AI will play a crucial role in future economic and social advancements (Xu et al., 2008; West & Allen, 2018; Georgieva, 2024). Not only has AI been a big helping hand for quotidian tasks, but it has also prompted a major movement in social development. (N. Duan et al., 2019) Eickhoff and Zhevak (2023) describe the integration of AI in advertising “In the context of marketing, Artificial Intelligence is employed for multiple purposes, including predicting future trends, assessing and contrasting various marketing channels, and customizing promotional communications (Kulkov, 2021; Eickhoff and Zhevak, 2023)

Nonetheless, AI is not a singular entity; it's an umbrella term encompassing a range of powerful subfields. The following figure will illustrate the relationships between key terms like Machine Learning, Generative AI, and Deep Learning - and how they all fit under Artificial Intelligence.

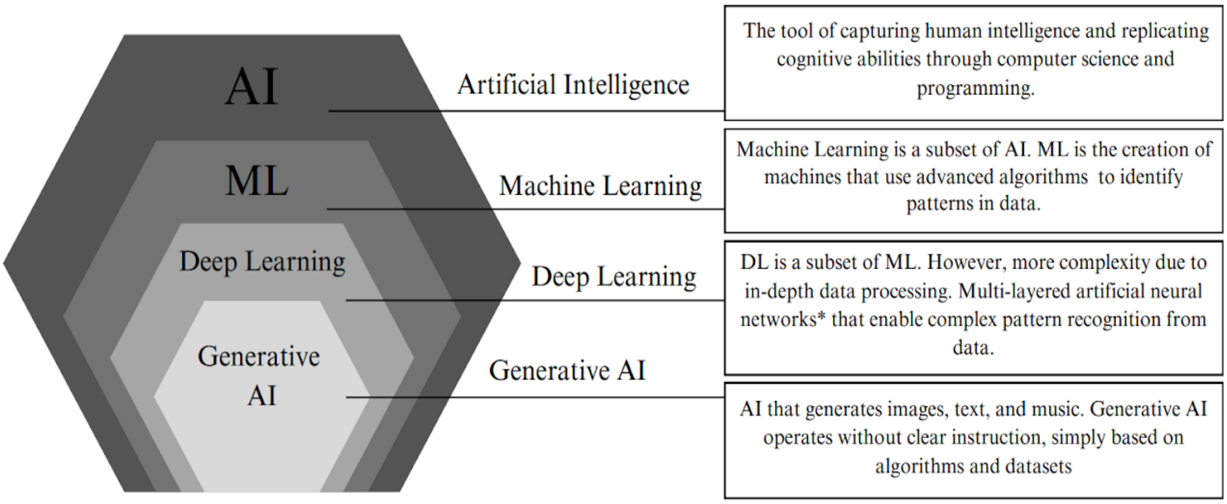

Figure 3: The Terminology of Artificial Intelligence

Note: Artificial Neural Networks* are an artificial replica of neural networks and sensory processing in the brain. (Krogh, 2008)

Source: Compiled by the author based on Zhuhadar, Lytras (2023); Devoteam, (2024)

Machine Learning, the foundation of many AI applications, equips the system with the ability to learn from data without explicit programming. In advertising, this translates to algorithms that can analyze customer demographics, browsing habits, and past purchases to predict what kind of ads will resonate most. Deep Learning is a subset of Machine Learning. It utilizes complex artificial neural networks to identify even more detailed patterns within data. This allows for highly personalized ad experiences, such as dynamically generated product recommendations or customized ad creatives based on individual user profiles. Lastly, Generative AI, another significant branch of AI, distinguishes itself by its ability to generate entirely new content, overcoming the limitations of mere data analysis. Some of the content that Generative AI has been able to produce are images, poems as well as music. (Zhuhadar, Lytras, 2023; Devoteam, 2024; Martin, 2023)

This advancement of technology, more specifically Generative AI in the advertising industry, is affecting the traditional photographic content industry typically used for creating and producing advertisements. The undeniable growth of AI has been of utmost help regarding its potential impact on various industries (Campbell et al., 2020). A recent advancement in AI is the ability to generate images based on textual descriptions. This technology, known as text-to-image generation, allows AI to create a wide range of creative visuals with brief guidance in the form of a description. The text-to-image generators fall under the Generative AI category. The reason AI-generated imagery has increasingly been integrated into the advertisement industry is due to the fact that some forms of Generative AI are nearly impossible for the human eye to distinguish from reality. (Floridi 2018; Karnouskos 2020; Kietzmann et al. 2020) Therefore, it can pose as a good alternative to the traditional resources used for photography.

Companies such as Microsoft, whose “Future of Work” campaign depicted innovative workplace scenarios, and Netflix, which has experimented with AI-generated movie posters, have discovered alternative approaches to traditional advertising photography by leveraging AI-image generation. It is evident that AI imagery saves resources and enables creative options that are not always possible with traditional photography. (Causevic, 2024) Several online platforms, such as Midjourney and DALL-E 3, have made these generative deep-learning models accessible to a wider audience, allowing experimentation among different audiences interested in engaging with this new technology (A. Smith & Cook, 2023). The process of experimentation in generating AI-images lies in a user’s skill in developing a textual command to input into the software to be presented with the artificially created outcome (Enjellina et al., 2023).

Generative AI is a relatively recent development within the technological landscape. As such, the field of AI image generation is still ongoing testing, research, and development. Various platforms demonstrate distinct strengths in generating images, nevertheless, they also possess inherent limitations such as difficulty achieving perfect photorealism as well as difficulty in creating realistic humans.

While some Generative AI platforms have the ability to create never-seen-before new human faces, the downside is the inaccuracies of the detailed qualities characteristic of humans (eyes, fingers, mouths, skin texture, facial expressions). Generative AI has not been able to completely generate images of humans with a perfect set of teeth or a set of 10 fingers. (Team, F. 2023). Despite advancements, Generative AI systems have yet to achieve the capability to consistently produce images that resemble reality. These limitations represent a significant barrier to the complete adoption of AI within the photo and image production industry.

In the table below the most significant disadvantages and shortcomings of generative AI are presented. (Smarty, 2023)

Table 2

Disadvantages and shortcomings of Generative AI software

Source:	AI software	Lack of accuracy (people, text)	Ethical concerns	Limited application/ Poor usability	Limited creativity	Resource-intensive (time, compute power, energy)
Guinness, (2024); Patel (2024)	DALL-E 3	X	X	X	X	X
Guinness, (2024); Maker, A., (n.d.)	Midjourney	X		X	X	
Gopinath.R, (2023); McKeag, (2023)	Stable Diffusion		X	X		X
Guinness, (2024); Helyer, (2023)	Adobe Firefly	X		X	X	
Guinness, (2024); N. Patel, (2023)	Generative AI by Getty	X			X	

Source: Team, (2023); *Firefly Really Poor at Generating People Images, and Following Scene Instructions.*, (2024); Guinness, (2024); N. Patel, (2023); Helyer, (2023); Maker, A., (n.d.); Gopinath.R, (2023); McKeag, (2023)

This table presents the various shortcomings and disadvantages inherent to current AI image generation tools. The X represents the disadvantage of the given software. Despite the diversity of these tools, several key indicators showcase the limitations. The most prominent limitations include a lack of accuracy in producing realistic images, restricted application scope, and limited creative potential. This limited creativity stems from the inability of AI to engage in independent thought or generate images that deviate significantly from the underlying training data. In the research by Eickhoff and Zhevak (2023) an experiment was done to test the correlation of AI-usage and consumer behavior, and the results indicated that AI was positively correlated with purchase intention. Wu et al. (2020) conducted research comparing human-generated and AI-generated art (including poems and paintings). Their findings indicated a stronger preference for human-generated art among American consumers.

Some direct measurement techniques for CPV have been measured by assessing AI-generated imagery through Likert-Scale questions and directly comparing traditional imagery/photography to AI-generated imagery (Bellaiche et al., 2023). In the research by Sweeney and Soutar (2001), the PERVAL model collected the data through focus groups, questionnaires, and telephone surveys, which resulted in the analysis of data through a comparative analysis. In Eickhoff and Zhevak (2023) research, a deductive approach for understanding consumer attitudes with the correlation of purchase intention based on AI images was used. The deductive approach employed using a combination of dichotomous, measurement and contingency questions (Likert-Scale, observability measures, purchase intention, attention-check question, etc.) (Eickhoff and Zhevak, 2023). While Likert-Scale questions has been a prominent measurement technique of consumer perceived value, the downside is that the consumers are aware that they are comparing AI-generated imagery to real photography. However, the author will assess consumer perceived value without directly telling the consumer which photo is a realistic photograph and which is AI-generated.

Having established the theoretical foundation, the author now turns to the empirical analysis and experimentation phase.

2. Testing the Utilization of AI-generated Imagery in Advertisements.

2.1.The Data and Methodology of the Experiment

In the empirical part of this thesis, the author will conduct an experiment to gather material to assess whether marketing/advertising industries in companies could opt to use AI-generated imagery instead of delegating resources to create a real photograph/image. This research prioritizes the role of backgrounds within the study. The empirical analysis will center on the creation and evaluation of background images. The conclusions will be drawn based on the results of the experiment that will be conducted by the author in the next chapter of this thesis.

The author predicts that the result of the experiment will demonstrate a higher evaluation of the advertisements utilizing realistic images as opposed to the AI-generated ones. The author predicts that subconsciously, the participants will detect the quality difference between AI imagery and realistic photography without being able to directly compare the two. The empirical part will be divided into two main components, focusing on:

1. The creation of AI-generated images and surveys for the experiment.
2. The collection of the data, doing descriptive statistics and generalizing findings.

This structure refers to the process of experimentation and the gathering of results and finally, tying to the findings to the literature review. In the first part, this research employed a quantitative approach, utilizing two self-administered surveys developed and distributed by the author through Google Forms. In the initial stage, the author established a mid-range strategy in terms of the prices for the products, with the price points between $50 and $500.

This approach was supported by prior market research focused on easily replicable popular products and their corresponding advertisements. The primary challenge involved sourcing product photographs and selecting appropriate backgrounds that would effectively highlight the products without introducing visual distractions. The author used AI image detection tools (Clarifai.com and Google image search) to ensure that the realistic photos that were used for the comparison were indeed real photography. First, the products were selected, and thereafter, the products were cut off from their original background using a background remover. The existing background was used as a stencil for creating the artificially generated images.

The author used the services Astica.ai, Deep.AI, and Pixlr.com to generate artificially generated photos for the survey content. Firstly, the author used the image description platform Astica.ai, where thereafter, the descriptions provided were used as a prompt in an AI text-to-image service. The author pasted the original product background into the software and was provided with a textual description of that image. While AI image description platforms were useful and provided a proper description of the image, the results of the images that were based on the textual descriptions, were not sufficient for the author's liking. Thereafter, the author found AI image-to-image services that recreated the photo of the original image with AI. This service provided images that were almost identical to the original product slightly deviating from reality. This made the images better for comparison purposes.

The AI image-to-image platform was Getimg.ai, and despite there being an original image to recreate, the platform also required a brief textual reference such as "*A man in black running"* or "*a landscape of mountains and a sunset*". In the table below, a few examples of the keywords used for image-generating prompts are presented:

Table 3

Keywords for AI-generated image prompts

Original image:	The keywords:	The AI image generated:
	“Green tennis court.”	
	“Sunset view from a restaurant.”	
	“Sunny sky, blue water beach.”	

Source: Compiled by the author (Appendix B)

The author will refer to AI-generated images as “artificially generated” in the empirical part of this research. The artificially generated image was taken, and the original product image was pasted onto the new AI background. That was the prototype for the “Artificially Generated Image.” The author used Graphic Design Software, Canva to create an advertisement for the images by adding text and other necessary information found in advertisements. In total there were eight images in each of the tests, which can be found in Appendix A. The tests for the experiment were set up as A/B tests, a commonly employed methodology for comparing variations. A/B testing commonly referred to as split testing, is an approach frequently utilized to compare two groups or versions to determine which is the better performing one. (Desk, 2024) This systematic approach allows researchers to divide an audience into two groups, each exposed to a different version (version A or version B), and subsequently measure their responses or behaviors. In this context, the author assessed the distinctions or similarities between pairs such as 1A (AI-generated) vs. 1R (Realistic Image) and 2R vs. 2A, etc. Each test presented participants with a series of eight images alternating between realistic photographs and artificially generated images. The number of images selected for the test is based on the author's preference for sufficiency, along with generalizing the findings. To minimize distribution bias, the author generated two separate surveys and shared both links within a single social media post. While URL redirection services are typically used for shuffling and randomizing A/B tests, the author deemed it unnecessary in this case. The questionnaires were then distributed for snowball sampling across various platforms such as Facebook, LinkedIn, Instagram, and WhatsApp. The test was constructed of multiple-choice questions, with the option to choose from five pre-determined prices displayed below the image. All of the products were chosen from a scale of $50 - $500 dollars. These prices were carefully selected using an Excel spreadsheet and ranged from 60% to 140% of the product's original price, with increments of 10% and 100% representing the actual cost (Appendix B). The table presents five prices (out of nine) chosen through random selection (highlighted in blue). In order for the author to generalize the findings, random sampling was used. The tests were the following: Consumer Perceived Value Test #1 (named: Perceived Value Test) and Consumer Perceived Value Test #2 (named: Perceived Value Questionnaire). The structure of the test was the following:

Table 4

Structure of the tests for the experiment

Perceived Value Questionnaire	**Perceived Value Test**
1A - Artificially generated image	1R - Realistic image
2R - Realistic image	2A - Artificially generated image
3A - Artificially generated image	3R - Realistic image
4R - Realistic image	4A - Artificially generated image
5A - Artificially generated image	5R - Realistic image
6R - Realistic image	6A - Artificially generated image
7A - Artificially generated image	7R - Realistic image
8R - Realistic image	8A - Artificially generated image

Note: To disguise the study's objective, participants received one of two **differently named** tests, preventing direct image comparison, and hindering their ability to discern the experiment's true purpose.

Source: Compiled by the author

The participants were instructed to select the price that, in their opinion, best corresponded to the value of each image; “*For this image, select the price that you believe best reflects the product's value.*” This process enabled the author to gather data on advertisement valuation through consumer perceived value. The goal was to measure whether the image in the first test (Perceived Value Questionnaire) 1A, which presented the artificially generated image was perceived to have a higher value than the corresponding image in the second test (Perceived Value Test) 1R, which was a realistic depiction of the same image.

The price list in the questionnaires were organized using the controlled randomization function, to ensure the prices were thoroughly shuffled. The surveys were in circulation from the 2nd to the 5th of April, a total of three days, and both tests gathered data from 125 respondents. A total of 250 participants (S = 250). The data collected through Google Forms was automatically populated into a MS Office Excel spreadsheet, facilitating its following data analysis stage. All of the respondents’ data was stored, kept, and used as each of the respondents managed to answer all of the required answers and submit the test successfully. The data analysis process involved:

1. Downloading the collected data from Google Sheets into MS Office Excel format.
2. Performing data analysis: descriptive statistics and comparison of tests in Excel.
3. Including a visual presentation of the data.

The author’s goal was to gather unbiased opinions on the products’ values without demographic factors influencing responses. This allows the author to focus on the perceived value of the respondents. Demographic questions were intentionally avoided to ensure participants were not swayed by factors like income, age, sex, etc. This allowed the author to analyze clear and raw answers. The author thinks that AI-generated imagery could substitute real imagery because this strategy has already been incorporated into many companies' advertisement creation processes.

2.2. Analysis of Results from the Experiment

The second part of the empirical part consists of a statistical analysis of the similarities and dissimilarities of the test results, leading up to the generalization of findings. While demographic information was not explicitly requested from the respondents in the questionnaires, the author suspects the sample primarily consisted of students. This assumption comes from the author's current social circle, which consists largely of university students. Descriptive statistics were performed variable by variable and then compared (the variable is the product in the advertisement). The comparison of the variable prices would provide an overview of how accurate the CPV prices were in respect to the products' original prices. The descriptive statistics provided the following information: Mean, Standard Error, Median, Mode, Standard Dev., Sample Variance, Kurtosis, Skewness, Range, Minimum, Maximum, Sum, and Count (Appendix B). To find out the value with the highest frequency and the normality in the test results, the author compared the modes and the medians derived from the descriptive statistics of the two tests. The table presents the mode and the median compared to the products' original price.

Table 5

Realistic Images test results

Image / Product	Mode ($)	Median ($)	Original Price ($)
Beach Chair	**106.71**	**106.71**	177.85
Winter Jacket	139.07	**106.98**	**106.98**
Grill	**313.71**	**313.71**	**313.71**
Skis	96.6	**161**	**161**
Champagne	**87.65**	**87.65**	125.21
Tennis Rackets	152.96	178.48	254.93
Fitbit	**59.99**	**59.99**	49.99
Camera	**492.06**	**492.06**	**492.06**

Source: The gathered realistic image results (Appendix C)

In the table of results, it can be noted that a few of the perceived values are aligned with the original price of the products. The prices marked in bold represent similarities. Two out of eight products were correctly evaluated in terms of the original price (Grill and Camera). What can be noted is that in most cases the mode (the most frequently perceived value) and median (the middle value) were the same for the products. This suggests that people's perceptions of these products' value were evenly distributed meaning they were similar to each other.

In contrast, the products where the mode was different from the median were for the Skis, the Winter Jacket, and the Tennis Racket. For the Skis image, there's a discrepancy between the "original price" and the results. The median is closer to the original price, but the mode is much lower. This suggests a wider variation in prices for the ski image across the data sources. The evaluation data for the Beach Chair images is consistent, with the mode and median very close. The grill appears to have the highest "original price" which aligns with the statistics calculated from the image data. In some cases, the mode and median are identical, which can indicate that the data for that image follows a symmetrical distribution.

As opposed to the product images (Skis, Tennis Rackets, and Winter Jacket), where the mode and median are not identical, meaning that there are either outliers or a skewed distribution. This difference suggests a potential for outliers in the data, which are extreme values that can skew the distribution. In the Excel spreadsheet table of descriptive statistics (Appendix C), the Winter Jacket has negative skewness. The negative skewness represents a situation where most values fall above the average, with a few outliers on the lower end. For the real images, there were more cases of products being undervalued than overvalued (see tables 5 and 6).

Table 6

AI-generated Images test results

Image / Product	Mode ($)	Median ($)	Original Price ($)
Beach Chair	**106.71**	**106.71**	177.85
Winter Jacket	96.28	**106.98**	**106.98**
Grill	**313.71**	**313.71**	**313.71**
Skis	128.80	**161**	**161**
Champagne	87.65	**125.21**	**125.21**
Tennis Rackets	152.96	178.45	254.93
Fitbit	69.99	59.99	49.99
Camera	**492.06**	**492.06**	**492.06**

Source: The gathered AI-images results (Appendix C)

When comparing the results of the modes and the medians with respect to the original price, there are two instances where all the values were the same (mode = median = original price). In many cases, the mode was undervalued in respect to the original price. The only case where the product was valued higher than the original price was the case of the Fitbit. The modes and medians are identical in only two out of the eight products - an interesting discovery is that they are the most expensive products that were correctly evaluated. When the modes and the medians are the same, it can represent a central tendency and symmetric data. However, since six out of eight cases were different, it might be an indication of uneven data distribution or the potential for outliers in the dataset. The mode and median being different from each other may also represent one very dominant value among other values.

Notably in both tables, the most frequently perceived value (the mode) is often the same for each product. Interestingly, the table with results for real product images has more consistent values compared to the table with AI-generated images. This suggests that participants had a more uniform perception of the value of products shown in realistic images, whereas their perceptions were more varied for products with AI-generated backgrounds.

The mode represents the most frequent price point, indicating the popularity of the answer among respondents. In the case of this experiment, the mode for each product signifies the price point where a significant number of consumers are willing to buy a product. Both tables depicting similar mode values represent the central tendency among values between the two tests. This means that in most cases, the consumer perceived value of a product was identical for the AI-generated image and the Real image. In the first test, the value that was chosen the most for the Beach Chair was $106.71 (see table 5), with a frequency of 100. On the other hand, in the second test, the value that was selected the most was equally $106.71 (see table 6); however, the frequency was 102 (the frequency data retrieved from the test results, can be found in the appendix). This slight difference implies a minor tendency in preference toward the AI-generated image.

However, while the similarity of the modes between the AI-generated and real images provides a basis for comparison, it alone does not offer sufficient evidence to conclude which image was valued higher. The author thereafter employed an approach, where the number of participants that selected a particular value was divided by the total number of participants and multiplied by 100 to derive percentages. This calculation enhanced the perspectives of comparison. The calculations were populated into the table below.

What can be understood from this percentage computation is that despite the modes being the same for both test cases, the only instance where the AI-generated image was valued higher than the realistic image was in the case of the Beach Chair (80% vs. 81.6%).

Table 7

The frequency of the values (%)

Product	Beach Chair	Grill	Champagne	Tennis Racket	Camera
Real	80%	29.6%	51.2%	46.4%	31.2%
AI	81.6%	27.2%	36%	44.8%	27.2%
The difference	**1.6%**	**2.4%**	**15.2%**	**1.6%**	**4%**

Source: Compiled by the author

This finding might be due to the novelty of AI-generated visuals or limitations in the current AI image generation technology. These results can be traced back to Turatto and Galfano's (2000) research outcomes, where the combined influence of color, shape, and effect could influence purchase intent. Purchase intent can be linked to consumer perceived value in this case since, as mentioned in the first stage of CPV by Monroe (1990), the value is determined before purchase. Monroe's (1990) as well as Lohse and Rosen's (2001) research indicated a positive correlation between high color contrast and human attention and high consumer engagement. When comparing the images of the Beach Chair, where the results were different from the rest (AI was higher-valued than the realistic image), then the key difference between the two images is color saturation. The light blue waterbody color in the AI-generated Beach Chair could have provoked a "vacation" effect that could have led to higher perceived value. Another theory that the author suspects is linked to Muehling, Sprott and Sultan's (2014) findings, where nostalgia themed advertisements led to a higher inclination to buy from the consumer perspective. The bright and highly saturated image in the Beach Chair advertisement could have created a subconscious link between the vivid colors and feelings of childhood nostalgia within the respondents' minds. The author acknowledges that the selection of the AI-generated photo in this scenario aligns with this explanation.

Nonetheless, the rest of the calculations indicate that the realistic image is valued higher than the AI-generated images. The closest difference between the images was for the Beach Chair, where the AI-image score surpassed the realistic image by 1.6%. This example demonstrates the potential for AI to be equally effective, particularly when considering the resource benefits of using AI-generated backgrounds. For the image of the Grill, where the realistic image surpassed the AI image, the realistic image received 29.6%, and the AI image received 27.2%; the percentage difference was 2.4%. The biggest difference between the scores was for the Champagne, with a percentage difference of 15.2%. Figure 4 represents a visual depiction of the previous calculations.

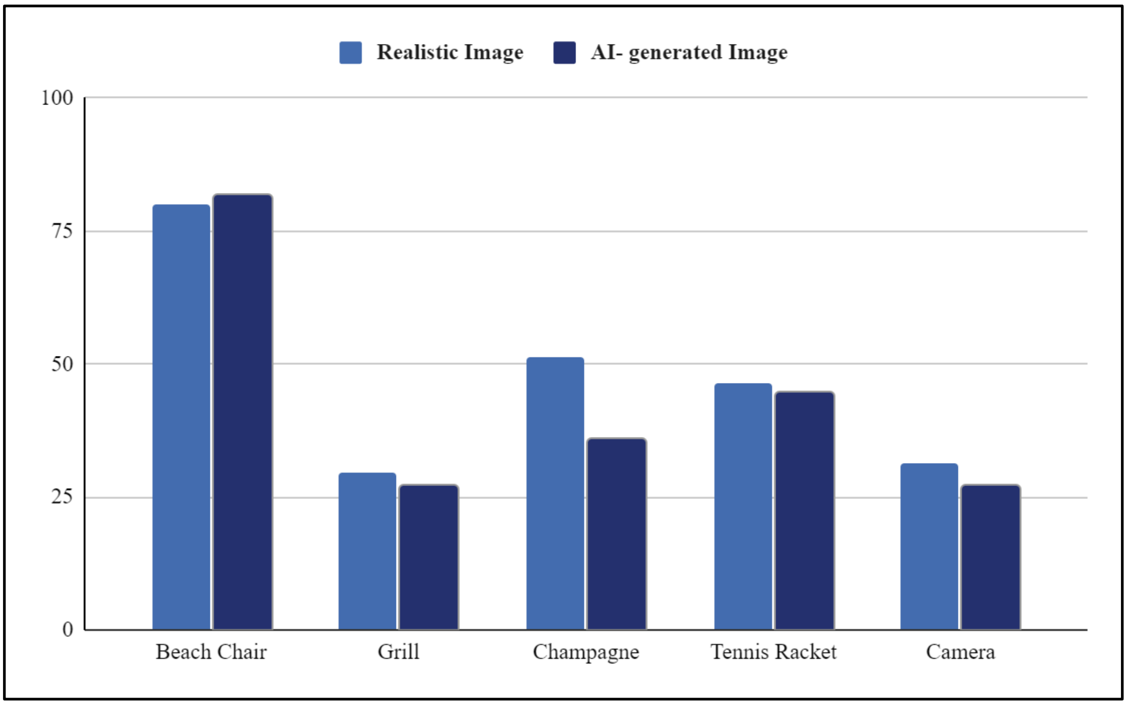

Figure 4: Visual representation of the frequency of values (%)

Note: The vertical axis depicts percentages.

Source: Compiled by the author

As the Champagne image caught the author's attention, with the percentage difference of 15.2%, the author found that this significant difference is the result of the selected prices from the price sheet (in the annex). While the trend for price selection was to select two prices below the original price and two over, leaving the original price in the middle. In the case of the Champagne image, three out of five prices were selected higher than the original price. This may have altered the results.

While the percentage computing and the figure above provide a thorough overview of the modes and the amount percentage of respondents that contributed to the highest frequency answer, then summarizations cannot be made of the mode solely. The mode solely indicates the value selected of highest frequency; however, it does not indicate the 50th percentile of the given values (which is distinctive to the median) (Gaddis & Gaddis, 1990). Retrieving the median from the descriptive statistics gives an overview of the middle value of the given values. In this case, the middle value represents the CPV. The median value of both real and AI images can be compared to the original price of the product by calculating the difference between the two. The broad percentages are computed by dividing the respondent

CPV with the original price. For example, the Beach Chair's original price was $177.85, therefore, the median percentile would be 100%. If the CPV was overvalued, then the percentile would be up to 140%. In the example of the Beach Chair product, the median value in percentages for the real image is 95% while the AI image is 60.05%. The difference between the percentages is 34.95%. Both percentiles are an indication of the CPV of the product in respect to the original price. Another observation for the Beach Chair case is that they are both undervalued in respect to the original price of the product. The next section will depict a graph of the difference of the medians of the actual value.

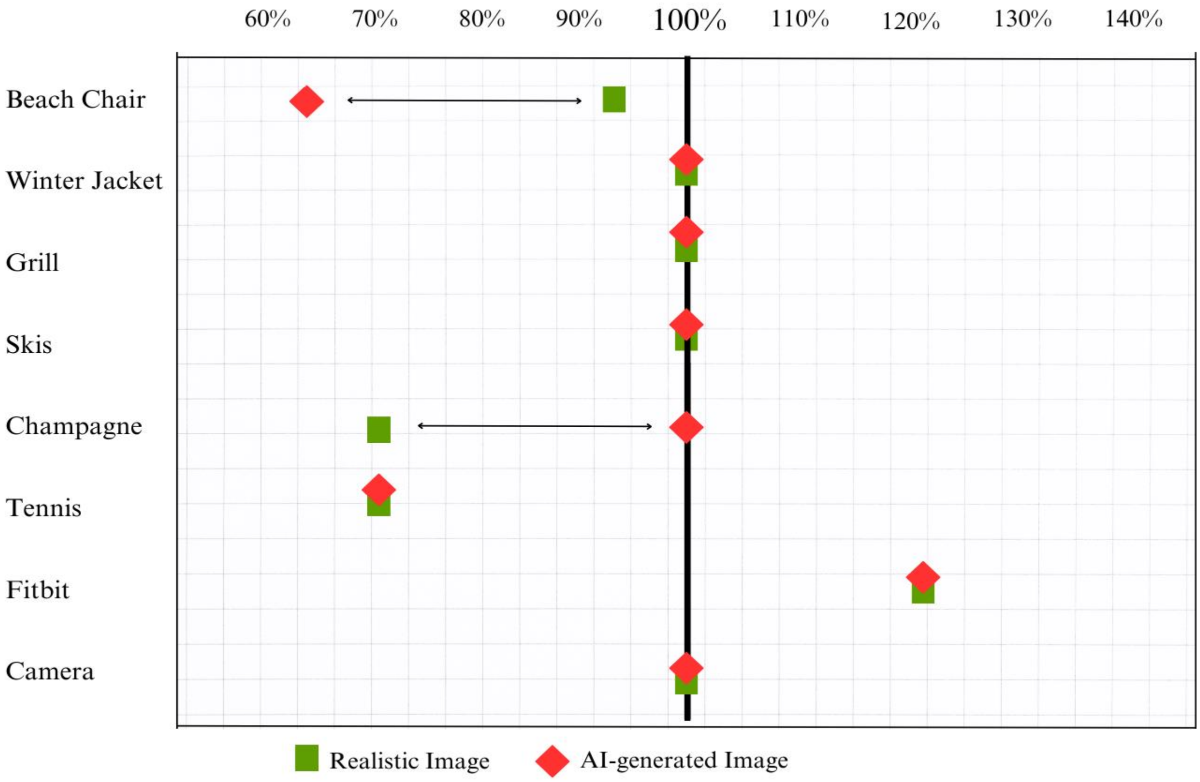

Figure 5: The medians of both AI-generated and Real Images

Source: Compiled by the author

The difference in medians is notable in only two cases. The double-sided arrow on the graph indicates a significant difference between the median value of the realistic image versus the AI-generated image. For the Beach Chair, the median was 95% for the real image, and 60.05% for the AI image, making the difference 34.95%. A similar pattern emerged for the champagne, where the real image held a median of 70%, while the AI-generated version reached a median of 100% - a difference of 30%. In both circumstances, the differences are less than 50%, suggesting that the overall magnitude of the discrepancies might be moderate.

The purpose behind testing consumers’ valuation on different advertisements was to identify and thereafter make the conclusion of whether AI-generated images could be a viable alternative to real photographs, potentially leading to resource savings for companies in terms of hiring models, photographers, designers, and photo editors. Other than AI-generated imagery being a viable resource-saving method for advertisements, the expediency aspect of having AI generate images deserves further consideration as well.

The results of the analysis of the modes showcase that CPV is higher when the background image is realistic. However, when comparing the medians to each other, it can be noted that the difference between the results is not drastic (less than 50%). The results can be interpreted in two contrasting ways.

Firstly, based on the first round of descriptive statistics by assessing the modes, where CPV was demonstrably higher in the cases of the realistic photos compared to AI-generated ones, the assumption can be made that AI-generated imagery needs to be modified and developed before it can completely overtake realistic photography in advertising. However, the further analysis of the medians revealed similar results between the two image types (Artificial vs Real), which prompts a second assumption suggesting that for some companies, utilizing AI-generated visuals could represent a resource-saving alternative to acquiring or creating realistic photographs for advertisements. Since the median evaluation scores did not show a significant enough advantage for companies using real images, the consolidation of resources with efficiency of AI-generated options can become more compelling. Therefore, the possibility remains, that AI-generated images can become a substitute for real images.

Now that the author has completed their research, they will discuss opportunities for future research. The selection process of these prices used to determine the consumer perceived value in this context and ad valuation presents a valuable opportunity for further investigation. A limitation of this study is that it relied solely on quantitative data to assess CPV. While the analysis of modes and medians provided valuable insights, it cannot fully explain the reasoning behind participants' valuations. A qualitative approach could be used to further understand why the participants valued the AI-generated image differently from the real image despite being unaware of a comparison between the two.

While this survey experiment demonstrated that realistic imagery may be perceived more favorably (based on the results and findings), it is essential to acknowledge the limitations of questionnaires. Questionnaires can provide valuable insights, but they may not capture the full picture of CPV. A qualitative approach of selecting a smaller sample size but asking how the respondents made the decision of selecting the specific price could lead to a more detailed understanding of what prompts price selection and CPV in respondents. Understanding how participants arrived at their valuations, particularly for cases where the AI-generated image received a different score, would be crucial for optimizing AI-generated images for advertising effectiveness.

In order to gain a deeper understanding on the subject of how participants engage with the background imagery, future research opportunities could employ eye-tracking experiments. This would reveal not only if participants were emotionally connected to the background but also whether they pay attention to it at all. Furthermore, this research focused on evaluating Consumer Perceived Value and the subconscious comparison of AI-generated imagery to real photography. Building upon this foundation, future research could explore the correlation between perceived value and various demographic factors, such as age, sex, and income - factors that were not included in this research. Analyzing these variables could help to understand consumer decision-making processes and potentially reveal whether demographics influence the perceived value of products presented with AI backgrounds compared to real ones.

Conclusion

Digital advertisements and AI-generated content represent two of the most prominent recent advancements within the field of technology. Combining the two results in a powerful combination, that has the ability to shape and change the marketing and advertising industries. The emergence of Generative AI and more specifically, AI-generated imagery, has induced significant research interest. Previous studies have investigated its impact on various factors, including consumer engagement, consumer reaction to manipulated advertising, and the creation of frameworks for understanding responses to AI-generated imagery. However, the lack of research in the field of measuring consumer perceived value (CPV), based on AI-generated images compared to real images was the inspiration for this experiment. The experiment compared the consumer perceived value of the products presented with AI-generated backgrounds versus real photographs.

The gap in existing research of measuring AI-generated advertisement image effectiveness with consumer perceived value was understudied, therefore, this research contributed to the current understanding of AI-generated imagery and consumer perceived value. This research addresses a gap in the literature concerning the implications of AI-generated advertisement images on consumer perceived value. By employing CPV as a metric, this study contributed to a more advanced understanding of how consumers perceive products advertised with AI-generated images. This thesis investigated the potential for AI-generated imagery to replace real photographs/images used for backgrounds in digital display advertisements.

In order to gather the consumer perceived value, a scale of prices was presented from which each respondent was tasked with selecting a suitable answer. The study analyzed how 250 participants perceived the value of advertised products (CPV) with real background as well as AI-generated images. Although the participant demographics were unknown, the author suspected that mostly students participated.

Descriptive statistics were used to analyze each product individually. The analysis focused on comparing the most frequently perceived value (mode) and the median value with the original price. In most cases, the most frequent perceived value was lower than the real price, indicating a potential underestimation of product value. The results suggested that for some consumers, there is no significant difference in perceived value between the two image types. Although, the results of the analysis of the modes showcase that CPV is higher when the background image is realistic. However, when comparing the medians to each other, it can be noted that the difference between the results is not drastic, which suggests that while AI-generated images may require further development to fully compete with realistic photography/images, they hold promise as a resource-saving alternative for advertisers. The successful implementation of AI-generated backgrounds in advertisements could lead to a strategic reallocation of resources within marketing departments.

The limitations of this study, such as the reliance on questionnaires and the exclusion of demographic factors, enable future research opportunities. Exploring qualitative approaches, employing eye-tracking experiments, and incorporating demographics into the analysis are all possibilities for further investigation of the topic.

In conclusion, this thesis demonstrates the potential of AI-generated imagery in advertising and how consumers subconsciously perceive products advertised with AI-generated images. It provides a foundation for future research to explore the complex relationship between AI-generated imagery and consumer perception.

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Appendices

Appendix A. Questionnaire of the survey as displayed to the respondent.

This survey is for the purpose of Isabella's bachelor's thesis.

Dear Participant,

Thank you for your interest in participating in this research study! The purpose of this survey is to investigate different advertisement valuations.

Your responses will be kept confidential and anonymous. They will only be used for research purposes and will not be disclosed to any third party. The data will then be deleted after defending my thesis.

This survey consists of ***8 questions*** *and should take approximately* ***3 minutes*** *to complete. If you have any questions or concerns about this survey or the research study in general, please do not hesitate to contact me, Isabella Abolrous, at* ***isabellaabolrous@gmail.com****.*

By proceeding with this survey, you indicate that you have read the above information, understand the purpose of the study, and consent to participate.

Thank you for your participation.

Sincerely,

Isabella Diana Abolrous

The University of Tartu DMS

Appendix B. Pricing scheme for the experiments

Table 4

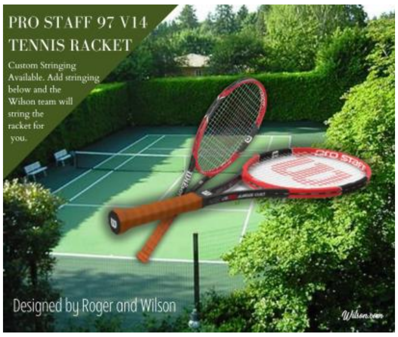
Pricing Scheme for the experiments

Product	**60%**	**70%**	**80%**	**90%**	**100%/ OP**	**110%**	**120%**	**130%**	**140%**
Chair	$106.71	$124.50	$142.28	$160.07	$177.85	$195.64	$213.42	$231.21	$248.99
Jacket	$64.19	$74.89	$85.58	$96.28	$106.98	$117.68	$128.28	$139.07	$149.77
Grill	$188.23	$219.60	$250.97	$282.34	$313.71	$345.08	$376.45	$407.82	$439.19
Skis	$96.60	$112.69	$128.80	$144.90	$161	$177.10	$193.20	$209.30	$225.40
Champagne	$75.13	$87.65	$100.17	$112.69	$125.21	$137.73	$150.25	$162.77	$175.29
Rackets	$152.96	$178.45	$203.94	$229.44	$254.93	$280.42	$305.92	$331.41	$356.90
Fitbit	$29.99	$34.99	$39.99	$44.99	$49.99	$54.99	$59.99	$64.99	$69.99
Camera	$295.24	$344.44	$393.65	$442.85	$492.06	$541.27	$590.47	$639.68	$688.88

Source: Compiled by the author
Note: OP - Original Product Price

Table 3

Keywords for AI-generated image prompts

Original image:	The keywords:	The image generated:
	"Green tennis court."	
	"Sunset view from a restaurant."	

<table>
<tr><td>
</td><td>“Scenic mountain view behind a lake with a sunset.”</td><td>
</td></tr>
<tr><td>
</td><td>“Sunny sky, blue water beach.”</td><td>
</td></tr>
<tr><td>
</td><td>“White winter forest.”</td><td>
</td></tr>
<tr><td>
</td><td>“Runner running with cliffs in the background.”</td><td>
</td></tr>
<tr><td>
</td><td>“Mountain range.”</td><td>
</td></tr>
</table>

	"Garden."	

Source: Compiled by the author

Preview of the test:

For this image, select the price that you believe best reflects the product's value.	**For this image, select the price that you believe best reflects the product's value.**
	
• $152.96 • $178.45 • $254.93 • $305.92 • $331.41	• $152.96 • $178.45 • $254.93 • $305.92 • $331.41

Source: Compiled by the author

Appendix C. Descriptive statistics

Table 5 reference

Test 1 - Realistic Images

Chair		Winter Jacket		Grill		Skiis	
Mean	113.68256	Mean	115.5366	Mean	317.4744	Mean	152.4992
Standard Error	1.817126803	Standard Error	2.502138	Standard Error	6.053574	Standard Error	3.963036
Median	106.71	Median	106.98	Median	313.71	Median	161
Mode	106.71	Mode	139.07	Mode	313.71	Mode	96.6
Standard Deviation	20.31609528	Standard Deviation	27.97475	Standard Deviation	67.68101	Standard Deviation	44.30808
Sample Variance	412.7437273	Sample Variance	782.5867	Sample Variance	4580.719	Sample Variance	1963.206
Kurtosis	19.27929657	Kurtosis	-1.04287	Kurtosis	-1.43038	Kurtosis	-1.06294
Skewness	4.196589138	Skewness	-0.37719	Skewness	-0.01062	Skewness	0.264236
Range	124.5	Range	85.58	Range	188.22	Range	128.8
Minimum	106.71	Minimum	64.19	Minimum	219.6	Minimum	96.6
Maximum	231.21	Maximum	149.77	Maximum	407.82	Maximum	225.4
Sum	14210.32	Sum	14442.07	Sum	39684.3	Sum	19062.4
Count	125	Count	125	Count	125	Count	125

Champagne		Tennis		Fitbit		Camera	
Mean	120.5025	Mean	200.6819	Mean	56.59	Mean	502.6882
Standard Error	2.498598	Standard Error	5.331551	Standard Error	1.10949	Standard Error	9.040102
Median	125.21	Median	178.45	Median	59.99	Median	492.06
Mode	87.65	Mode	152.96	Mode	69.99	Mode	492.06
Standard Deviation	27.93518	Standard Deviation	59.60855	Standard Deviation	12.40447	Standard Deviation	101.0714
Sample Variance	780.3743	Sample Variance	3553.18	Sample Variance	153.871	Sample Variance	10215.43
Kurtosis	-1.011	Kurtosis	-0.56367	Kurtosis	-0.51613	Kurtosis	-1.24423
Skewness	0.160835	Skewness	0.926147	Skewness	-0.6767	Skewness	-0.23385
Range	87.64	Range	178.45	Range	40	Range	295.24
Minimum	87.65	Minimum	152.96	Minimum	29.99	Minimum	344.44
Maximum	175.29	Maximum	331.41	Maximum	69.99	Maximum	639.68
Sum	15062.81	Sum	25085.24	Sum	7073.75	Sum	62836.03
Count	125	Count	125	Count	125	Count	125

Source: Compiled by the author using MS Excel

Table 6 reference

Test 2 - AI-generated Images

Chair		Winter Jacket		Grill		Skiis	
Mean	114.8207	Mean	116.3925	Mean	326.7599	Mean	156.3632
Standard Error	2.025416	Standard Error	2.573716	Standard Error	5.911195	Standard Error	3.8658
Median	106.71	Median	106.98	Median	313.71	Median	161
Mode	106.71	Mode	96.28	Mode	313.71	Mode	128.8
Standard Deviation	22.64484	Standard Deviation	28.77502	Standard Deviation	66.08916	Standard Deviation	43.22096
Sample Variance	512.789	Sample Variance	828.0018	Sample Variance	4367.778	Sample Variance	1868.051
Kurtosis	10.37666	Kurtosis	-1.11016	Kurtosis	-1.1814	Kurtosis	-1.01088
Skewness	3.280571	Skewness	-0.36031	Skewness	-0.375	Skewness	0.338509
Range	124.5	Range	85.58	Range	188.22	Range	128.8
Minimum	106.71	Minimum	64.19	Minimum	219.6	Minimum	96.6
Maximum	231.21	Maximum	149.77	Maximum	407.82	Maximum	225.4
Sum	14352.59	Sum	14549.06	Sum	40844.99	Sum	19545.4
Count	125	Count	125	Count	125	Count	125

Champagne		Tennis Rackets		Fitbit		Camera	
Mean	113.3911	Mean	202.7214	Mean	53.79	Mean	490.4855
Standard Error	2.608072	Standard Error	5.243372	Standard Error	1.24486	Standard Error	9.30159
Median	87.65	Median	178.45	Median	59.99	Median	492.06
Mode	87.65	Mode	152.96	Mode	59.99	Mode	492.06
Standard Deviation	29.15913	Standard Deviation	58.62268	Standard Deviation	13.91796	Standard Deviation	103.9949
Sample Variance	850.2546	Sample Variance	3436.619	Sample Variance	193.7097	Sample Variance	10814.95
Kurtosis	-0.86164	Kurtosis	-0.81704	Kurtosis	-1.16053	Kurtosis	-1.40614
Skewness	0.631863	Skewness	0.775407	Skewness	-0.42729	Skewness	0.05832
Range	87.64	Range	178.45	Range	40	Range	295.24
Minimum	87.65	Minimum	152.96	Minimum	29.99	Minimum	344.44
Maximum	175.29	Maximum	331.41	Maximum	69.99	Maximum	639.68
Sum	14173.89	Sum	25340.17	Sum	6723.75	Sum	61310.69
Count	125	Count	125	Count	125	Count	125

Source: Compiled by the author using MS Excel

Table of the median percentages

Median of product:	**Real:**	**AI:**
Beach Chair	95.00%	60.05%
Winter Jacket	100.00%	100.00%
Grill	100.00%	100.00%
Skis	100.00%	100.00%
Champagne	70.00%	100.00%
Tennis	70.00%	70.00%
Fitbit	120.00%	120.00%
Camera	100.00%	100.00%

Source: Compiled by the author using MS Excel

External Source Frequency Table:

https://docs.google.com/spreadsheets/d/1YP0Y1Me09WENi7h3xBml4m_KOR9oYHAF/edit?usp=sharing&ouid=102458846218656158994&rtpof=true&sd=true

Resümee

TEHISINTELLEKTI ABIL LOODUD REKLAAMPILTIDE KASUTATAVUS DIGIREKLAAMIDES

Isabella Diana Abolrous

Käesoleva lõputöö eesmärk oli välja selgitada võimalus asendada ehtsad fotod staatiliste reklaamide taustapiltide jaoks tehisintellekti poolt genereeritud piltidega. Reklaamitööstus on alates tehnoloogilisest revolutsioonist tohutult arenenud. Üks reklaaminduse harusid, mis on tänu internetilevikule kiirelt arendanud, on digitaalne reklaamitööstus. Reklaami digitaliseerimine on ajendanud ettevõtteid tõhustama paremaid viise informatsiooni kogumiseks kasutajate suhestumisest reklaamidega. Selle tulemus soodustab kliendi käitumise paremat mõistmist ning võimaldab ettevõtetel kavandada tõhusamaid reklaamikampaaniaid. Effektiivsete reklaamkampaaniate tootmine nõuab aga rohkelt ressursse. Seevastu saaks reklaamide tootmiseks kasutatud resursse suunata hoopis, ettevõtte jaoks alternatiivsete vajaduste rahuldamiseks, kui on olemas piisavalt võimas asendaja nagu naiteks Tehisintellekt (TI).

Tehisintellekt on vahend inimintellekti jäädvustamiseks ja kognitiivsete võimete jäljendamiseks arvutiteaduse ja programmeerimise abil. TI on tõestanud end valdkondades, mis on tavapäraselt olnud inimtööjõu pädevuseks. Tänu tehisintellekti kiirele arengule on paljud senised töökohad automatiseeritud. Tihti kardetakse tehisintellekti edusamme ja seeläbi alahinnatakse selle võimaliku arengut loominguliste ülesannete täitmisel. Generatiivne tehisintellekt on TI-tehnoloogia alarühm, mis suudab luua mis tahes erinevat tüüpi sisu (näiteks pilte, luulet, muusikat) ning see liigub aina lahemale realistlikuma pildi loomise suunas. Generatiivse tehisintellekti kiire areng on vähendanud lõhet ehtsa ja sünteesitud pildi vahel. See tõdemus ajendab uurima, kas realistlike reklaampiltide tajutav väärtus erineb tehisintellekti poolt loodud piltidest. See loob aluse selle uurimiseks, kas realistlike piltide reklaamide tajutav väärtus on erinev võrreldes tehisintellekti loodud piltidega. Siinkohal tõusetub küsimus, kas reklaami taustapildi loomisele kuluvaid ressursse on võimalik asendada lihtsa tehisintellekti tekst-kujutise generaatoriga. Tekst-kujutis viitab spetsiifilisele tarkvaras kasutatavale juhisele, mis võimaldab tekstilise kirjelduse põhjal luua originaalset visuaalset kunsti (Dehouche & Dehouche, 2023).

Uurimuse empiiriline osa jagunes kaheks peamiseks osaks, tehisintellekti poolt genereeritud piltide ja küsitluste loomine eksperimendi jaoks ning seejärel, andmete kogumine, kirjeldava statistika tegemine ja tulemuste üldistamine. Empiiriline analüüs keskendus taustapiltide loomisele ja hindamisele. Eksperimendi testid koostati A/B-testidena,

mis on tavapäraselt kasutatav metoodika variantide võrdlemiseks. (Desk, 2024) Selles kontekstis hindas autor erinevusi või sarnasusi selliste pildi paaride vahel nagu 1T (tehis) vs. 1A (autentne) ja 2A vs. 2T jne. Uuritavad muutujad olid mediaan ja mood. Väärtuste sageduse analüüsi tulemused näitasid, et tarbija poolt tajutav väärtus on suurem/kõrgem, kui taustapilt on autentne. Kui aga võrrelda mediaane omavahel, siis tulemuste erinevus ei ole suur (alla 50%). Tulemusi sai tõlgendada kahel erineval viisil. Enamus väärtuste sagedused, olid mõlemal juhul piltide puhul sarnased. Esiteks võib kirjeldava statistika esimese vooru põhjal, hinnates sagedust, kus tarbija poolt tajutud väärtus oli realistlike fotode puhul ilmselgelt kõrgem võrreldes tehisintellektiga loodud fotodega, teha oletuse, et tehisintellektiga loodud kujutisi tuleb muuta ja arendada, enne kui need saavad taielikult üle votta autentseid pilte. Kuid edasine mediaanide analüüs näitas sarnaseid tulemusi kahe pilditüübi vahel (tehis vs. reaalne), mis annab alust teisele oletusele, et mõndade ettevõtete jaoks võib tehisintellekti abil loodud piltide kasutamine olla ressursisäästlik alternatiiv. Kuna mediaanväärtused ei näidanud piisavalt olulist eelist ettevõtetele, kes kasutavad reaalseid pilte, võib ressursside koondamine koos tehisintellekti loodud võimaluste tõhususega muutuda veenvamaks.

Käesoleva töö eksperimendi tulemused annavad väärtuslikke järeldusi paarile peamisele sihtrühmale. Ettevõtete turundus- ja reklaamiosakonnad võivad saada ülevaate tehisintellekti loodud kujutiste kasutamisest sisu loomisel. Ettevõtete omanikud ja juhid võiksid mõtestada ümber ressursside jagunemise ja reklaamieelarvete üle. Lõpuks pakuvad eksperimendi tulemused väärtuslikke andmeid tehnoloogia arendajatele ja teadlastele, kuna tehisintellekti arendajad saavad tulemusi võtta tagasisidena ja luua kvaliteetsemaid ja tõhusamaid vahendeid pildi genereerimiseks, aidates lõppastmes kaasa tehnoloogia enda arengule. Selle uuringu piirangud, näiteks tuginemine ainult küsimustikele ja demograafiliste tegurite väljajätmine, võimaldavad edasisi uurimisvõimalusi. Kvalitatiivsete lähenemisviiside uurimine, silmade-jälgimiskatsete kasutamine ja demograafiliste andmete lisamine analüüsi on kõik võimalused teema edasiseks uurimiseks.

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