Research Article / Araştırma Makalesi

AI ART IN MOBILE: TOPIC MODELING OF USER REVIEWS FOR GENERATIVE AI APPLICATIONS

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ABSTRACT

The generative AI concept, which enables users to create text, image, and video content through prompts, is revolutionizing the content side and AI applications in marketing. Despite the increasing popularity of generative AI applications, the market perception regarding generative AI remains underexplored. This study aims to explore the generative AI market perception through the context of mobile applications with the help of user reviews. The study follows a structured approach including identifying the generative AI mobile applications, assessing the context through rating scores and install amounts of mobile applications, and using a topic modeling approach (BerTopic) for online reviews to identify the topics included in the conversation. 8159 user reviews from 22 mobile applications are used as sample of the study and the average rating score for the sample found as 4,06 which signals a positive perception of market. The study concludes top ten topics as; "Dissatisfaction About Amount of Advertisements in app", "NSFW Content and Moderation", "Praise of Application", "Functionality Problems & Crashes", "Payment Necessity and Trial Problems", "In-App Purchase Restoration Problems", "Specific Feature in App", "Chat Function", "Credit System" and "Excess of Ads". The study reveals the main issues of Ai Art mobile applications for marketing decision-making processes.

Keywords: AI Art, Generative AI, Artificial Intelligence, Mobile Applications, User Reviews

JEL Classification Codes: M30, M31

MOBİLDE YAPAY ZEKÂ SANATI: ÜRETKEN YAPAY ZEKÂ UYGULAMALARI KULLANICI YORUMLARININ KONU MODELLEMESİ

ÖZET

Kullanıcıların istemler aracılığıyla metin, resim ve video içeriği oluşturmasına olanak tanıyan üretken yapay zekâ kavramı, pazarlamada içerik tarafında ve yapay zekâ uygulamalarında devrim yaratmaktadır. Üretken yapay zekâ uygulamalarının artan popülaritesine rağmen, üretken yapay zekaya ilişkin pazar algısı yeterince araştırılmamış durumdadır. Bu çalışma, kullanıcı incelemeleri üzerinden mobil uygulamalar bağlamında üretken yapay zekâ pazarı algısını keşfetmeyi amaçlamaktadır. Çalışma, üretken yapay zekâ mobil uygulamalarının belirlenmesi, mobil uygulamaların derecelendirme puanları ve kurulum miktarları yoluyla bağlamın değerlendirilmesi ve sohbete dahil edilen konuların belirlenmesi amacıyla çevrimiçi incelemeler için bir konu modelleme yaklaşımının (BerTopic) kullanılması dahil olmak üzere yapılandırılmış bir yaklaşımı izlemektedir. Araştırmanın örneklemi olarak 22 mobil uygulamadan 8159 kullanıcı yorumu kullanılmış ve örneklemin ortalama derecelendirme puanı 4,06 olarak bulunmuş ve bu da pazar algısının olumlu olduğuna işaret etmektedir. Çalışmada ilk 10 konu olarak; "Uygulamadaki Reklamların Miktarı, Müstehcen (NSFW) İçerik ve Denetimi, "Uygulamanın Övülmesi", "İşlevsellik sorunları ve Çökmeler", "Ödeme Gerekliliği ve Deneme Sorunları", "Uygulama İçi Satın Alımların Geri Yükleme Sorunları", "Uygulamadaki Belirli Bir Özellik", "Sohbet İşlevi", "Kredi sistemi", "Reklamların Fazlalığı" tespit edilmiştir. Çalışma, yapay zekâ sanatı mobil uygulamalarının pazarlama karar alma süreçlerine yönelik temel konularını ortaya koymaktadır.

Anahtar Kelimeler: Yapay Zekâ Sanatı, Üretken Yapay Zekâ, Yapay Zekâ, Mobil Uygulamalar, Kullanıcı Değerlendirmeleri

JEL Sınıflandırması: M30, M31

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1. Introduction

Artificial intelligence-supported applications have become essential business applications of the last decade. New developments are experienced in productization processes, reflections on consumption patterns, and market reactions. Artificial intelligence, initially used as a tool for decision support processes on issues such as understanding certain data/situations and making models, has progressed towards different areas used to produce content such as text, visuals, and videos. A specific branch of AI technologies called Generative AI enables users to produce text, visuals, and videos through their requests with the help of AI systems. Generative AI refer to AI models class that help user to produce seemingly original outputs such as text, images, music, video and other media types (Ivanov et al., 2024). These new applications have become an important research topic due to their impact on the market and their economic potential.

The potential of generative AI applications in the market can be examined through economic and market perspectives. From economical perspective, Goldman Sachs (2023) research indicates adoption of the tools of tools in natural language processing by companies and society can lead to 7% increase in global GDP and can lift productivity growth by 1.5% over ten year period. This argument impacts society's market and labor side and affects the marketplace in a macro scope. From the market perspective, Bloomberg Intelligence report (Catsaros, 2023) states that generative AI market can grow to $1.3 trillion over the next ten years. This argument discusses how generative AI applications will be accepted/adopted in various markets/contexts/product groups. This study focuses on the market side of generative AI's potential and aims to examine the phenomenon in its first period/launch stage in the marketplace.

Theoretical side of the study refers to the AI-enabled systems and user interaction. Usage of AI-enabled systems included in the human-computer interaction phenomenon and continuous advances in AI technologies are related to new challenged and opportunities for this phenomenon (Amershi et al., 2019). The usage of products/services, improving the usability and user experience, satisfaction/dissatisfaction enablers are fundamental contexts for consumer research in future. This study answering the call of Oppenlaender (2023)'s future research directions suggestions focuses on the user-AI interaction side in terms of mobile applications context. Evaluation of the AI art mobile application market by the topics/content side refers to the study's aim in terms of the context.

The methodological side of the study refers to online reviews and a topic modeling approach. The study investigates the AI-art phenomenon (creating media content through text-based prompts) using word-of-mouth and user review contexts. AI-art mobile applications on the Google Play store are identified, and user reviews are obtained to examine the market perception regarding AI Applications. Previous studies (Hu et al., 2014; Siering et al., 2018; Li et al., 2019; Ma et al., 2022) utilize online reviews to understand market/consumer, and following the same approach, the study aims to examine the generative AI concept by user reviews. Evaluation of user reviews in the literature employs several methods such as text mining (Cao et al., 2011; Berezina et al., 2016; Lucini et al., 2020), sentiment analysis (Ireland & Liu, 2018; Zhang et al., 2021; Li et al., 2023), semantic network analysis (Oh & Kim, 2020; Oh et al., 2023) and topic modelling (Guo et al., 2017; Korfiatis et al., 2019; Guo et al., 2022). This study utilizes the topic modeling approach to asses the textual content as feedback and word-of-mouth mechanisms in the conversation consistent with the research aim. Topics included in conversation are detected and examined in the study to conclude the market implications of the topic. The study starts with literature review sections for generative AI and online review concepts, then includes the methodology and findings, and finalizes with a conclusion and future research directions.

2. Literature Review

2.1. Generative Artfifical Intelligence

The initial applications of artificial intelligence in business life were about calculating specific parameters, predicting certain results, and detecting and testing certain causal connections. In recent decades, a new agenda item has emerged for artificial intelligence applications focusing on understanding existing data, detecting patterns, and developing models. Based on existing data sets, studies have been carried out in various fields to produce data that are similar or close to the existing data set, and today, this subject is studied as generative AI. The technical side of generative AI for image generation includes two main routes: generation of new data and implementation to the image environment. The first part is related to generative adversarial nets (GAN) which includes two models; one for generative model that produces the fake data, while second model (discriminative) tried to detect the fake/real (Goodfellow et al., 2014). Second part refers to evaluation the images and Contrastive Language Image Pre-training (CLIP) as a visual model which has ability to optical character recognition, geo-localization and action recognition (Radford et al., 2021) was introduced for the visual side. In recent years, optimization of text-to-image generation has been test through zero-shot generation study of Ramesh et al. (2021) which is one of the significant concept for today's market.

For the conceptual side, Feuerriegel et al. (2024) define generative ai as *"to computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data."*. Generative AI relies on the massive amount of data and can generate output based on the user input (Sætra, 2023). In generative models, the produced data resemble the training data which is the opposite of classification algorithms that aims differentiation (Ali et al., 2021). Generative models also differs from discriminative models, as the discriminative models can detect/identify an object in an image, generative models can generate new images for the object (Pataranutaporn et al., 2021). For example, the user can write text content called "prompt" as "a landscape of Paris on a sunny day" to a Generative AI interface, and an image can be produced consistent with that prompt.

Produced content can refer to audio, video, code, image, text and simulations in generative AI (McKinsey & Company, 2023). The generation of individual content type refers to specific names such as text-to-image, text-to-video and so on. For example, text-to-image expression is called as "ai art" (Oppenlaender, 2023) refers to producing image output prompted by user input. For a broader perspective, AI art is defined in this study as leveraging of artificial intelligence-supported systems/softwares for generating outputs in the forms of entities, artistic styles and emotional expressions.

Text-to-image generation side of generative AI can be examined in dual perspectives which covers the creator side and customer/market side. For the creator side, Ko et al. (2023) examine large-scale text-go-image generation models in visual artists context and concludes the various usage of these models such as automation of the creation process, contribute to ideation, facilitating/mediating the communication. For the customer/market side, one of the significant ideas in generative AI is the open ecosystem that enables users around the world to contribute to generation and improvement of the models. In addition to giant actors in marketplace like OpenAI and Google, free models like Stable Diffusion (Stability AI, 2024) are also provided to online users. Basemodel of stable diffusion can be extended to custom models trained on custom datasets which makes a creative ecosystem in the world. Civitai platform (Civitai, 2024) hosts the customized image models for the users and users can download the models, share the prompts with community and showcase their produced images with others. Following te nature of open-ecosystem, there are many applications of generative AI in the marketplace which enables users to produce images.

Generative AI is important for marketing and business research because of the scope and speed of technological developments, the diversity of applications, and the economic potential. It would be helpful to learn how generative AI applications produced for end consumers are received by consumers, the identification of facilitating/complex factors regarding adoption, and the general attitude of the market. Based on this, this study aims to make inferences about the market through the context of online review, and the subject of online review is included in the next section.

2.2. Online Reviews and eWOM

A classic definition of word of mouth (WOM) by (Westbrook, 1987) is *"informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers."*. The social nature of humanity amplifies the word of mouth concept in marketing topics and it is more effective than the commercial messages. Main idea of effectiveness of WOM concept relies on the reality that sources are independent from the commercial influence (Litvin et al., 2008), as the communication is passed through "unbiased filter of -people like me-" (Allsop et al., 2007). In initial period word of mouth concept is limited by the social circle of people, however, popularity of social media platforms and internet leads to extension of communication reach in word of mouth concept. Users can share their experiences online to thousands of other people living around the world even they do not know anything about them. WOM concept is extended to electronic WOM concept in the last decades as Hennig-Thurau et al. (2014) include *"...made available to a multitude of people and institutions via the Internet."* extension in their eWOM definition in the study. They also include "potential, actual of former customers" section in the definition which emphasizes the large scope of the eWOM concept. The potential side of eWOM definition relies on the reality that people are examining the other's opinions about the products/services before they purchase the product/serbice.

eWOM concept has a dual nature consistinf of customer side and business side. The customer side of eWOM concept simply relies on the reality that consumers rely more on online discussions (or opinion of others) than the marketer-generated information (Bickart & Schindler, 2001). When the users are searching for any product/service information on web, they usually have access to dozens of other consumers' product reviews (Mudambi & Schuff, 2010). Online consumer reviews can be utilized as the sale assistant or marketing-mix element (Chen & Xie, 2008), they have two roles informants and recommenders roles (Park et al., 2007). On the other hand, business decision-making side of eWOM and online reviews mostly relies on understanding the marketplace, relationship and reactions. Since the online feedback mechanisms intensify the interdependencies between different actors in market (Dellarocas, 2003) and sensemaking of opinions and attitudes into actionable

decision-point sources can be helpful to companies in terms of launching new products or redesigning products and services (Barbosa et al., 2015), market structure / competitive landscape / features of company's and competitors' products (Netzer et al., 2012). Therefore, brands have a wide variety of online information sources to evaluate the marketplace, which requires the assessment of various general and niche data sources/platforms in the market. Combining dual sides, marketing decision-makers can use eWOM to understand customer communication regarding experience, recommendations, and so on. Therefore, they can direct their decisions to the feedback of the marketplace.

Employing online reviews content for understanding the market is utilized in several contexts including hospitality (Neirotti et al., 2016), airline (Stamolampros et al., 2019), sharing economy (Xu, 2020), e-commerce (Duan et al., 2022) in the literature. This study focuses on generative AI concept in mobile application context and the next section includes the methodological approach employed in the study.

3. Methodology

3.1. Research Approach and Data Collection

The study employs a three-stage approach for the methodology part. In the first part, relevant mobile applications for the study sample are defined by obtaining the list from the mobile application store. The code snippet below is employed to detect the AI art mobile applications in the Google Play Store. Search is the function's name for searching applications in the store, the lang parameter is used for English language applications, and the country parameter is used for selecting the applications in the United States store. Finally, the n_hits parameter is used as the default value for the number of applications.

$$result_{ai} = search("AI\ art", lang = "en", country = "us", n\_hits = 30)$$

This code query retrieves 24 mobile applications, and two of the applications are excluded from the sample since they are either only photo editor or do not have an AI focus. The remaining 22 mobile application names and categories are included in Table 1.

Table 1: Mobile Applications Sample in the Study

Application Name	App Category	Application Name	App Category
PixAI:AI Anime Art Generator	*Art & Design*	CreArt - AI Art Generator	*Art & Design*
WOMBO Dream - AI Art Generator	*Art & Design*	Illusion AI	*Art & Design*
Wonder - AI Art Generator	*Art & Design*	Remix: AI Image Creator	*Art & Design*
AI Mirror: AI Art Photo Editor	*Photography*	ARTA: AI Art & Photo Generator	*Art & Design*
Spellai - AI Art Maker	*Art & Design*	Dreamerland - AI Art Generator	*Art & Design*
starryai - AI Art Generator	*Art & Design*	monAI - AI Art Generator	*Art & Design*
AI Art Generator	*Art & Design*	Anime AI Art - Otaiku	*Art & Design*
GenZArt: Fast AI Art Generator	*Art & Design*	Yodayo	*Art & Design*
Gencraft - AI Art Generator	*Art & Design*	AI Art Image Generator – GoArt	*Photography*
ImagineArt : AI Art Generator	*Art & Design*	Lensa: photo editor & AI art	*Photography*
Photoleap: Photo Editor/AI Art	*Art & Design*	AI Picasso - Dream Art Studio	*Art & Design*

The second part focuses on the overall statistics of sample applications to evaluate the attitude of market to context. It includes descriptive stats to understand the overview of the AI art mobile applications and contains information such as mobile category application distribution, rating score distribution, rating scores by app categories, install amount distribution, install amount by categories. Finally the last part employs topic modelling methodology to examine the conversation in detailed level.

The data collection stage include the retrieving of data using Python (Van Rossum & Drake, 1995) programming language to get the data and using "Google-Play-Scraper" (Jo, 2019) python code package to retrieve

the user reviews from Google Play Store. The data collection takes place on 15th April 2024 and, total 8159 reviews of 22 applications are obtained for the study.

3.2. Methodology

There are three basic data types in user reviews of applications on the Google Play Store: textual data, rating score, and helpful score. The rating scores are used in the descriptive analysis part of this study, and the text part is used for the topic modeling part. Wide range of content in online reviews includes rating scores as numeric data, text messages in raw text data, photos or videos as the attachment to review content. The variety leads to evaluation of individual data types by consistent methodological approaches such as regression/correlations for numeric data, text mining/sentiment analysis/topic modelling for raw text data, computer vision methodologies for image and video data.

In general level, text mining can function as alternative analysis to human analysis for the text data, as it reduces human labor use for the tasks like classification and identification of key words in online reviews (Zhao, 2021). Specifically, topic modelling as text-type data methodology is a type of statistical modeling to detect topics included in the collection of documents and it is a unsupervised machine learning technique as the topics are not pre-defined (Meddeb & Romdhane, 2022). Documents are examined as a collection of topics and topics are examined as a probability distribution of words in this approach (Rani & Kumar, 2021). Traditional topic modelling approaches employs latent dirichlet allocation (LDA) topic modelling, however, in recent years transformers-models for language studies are becoming popular in the literature (Araci, 2019; Ray et al., 2021; Patel et al., 2023). This study employs a transformers-model developed for topic modelling specifically titled as BerTopic (Grootendorst, 2022) for detecting the topics included in the conversation.

4. Results

22 mobile applications in the study have to main categories; 19 for arts & design, 3 for photography categories. Figure 1 presents the distribution of the categories as 86.4% for arts & design and 13.6% for the photography category. This finding indicates that mobile apps developer embed the generative AI mostly on art & design applications which enables users to generate images, while the minority of the apps belong to photography category where the applications combines the AI art with photography features in the apps.

Figure 1: Distribution of Categories for AI Art Mobile Apps
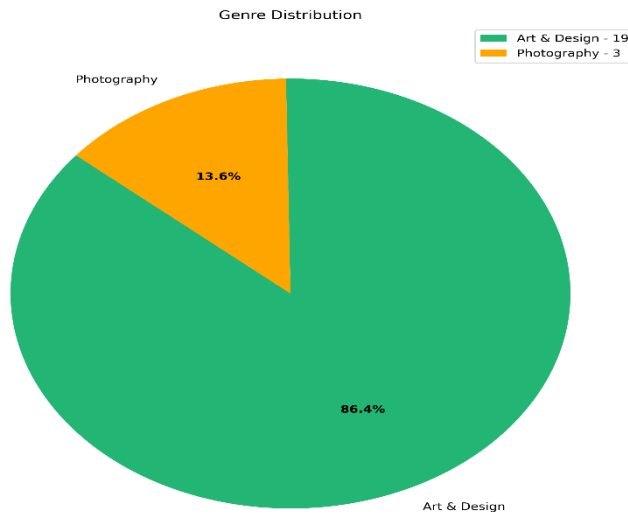
Following the category distribution, rating score averages for each application in the sample are evaluated to conclude an overvief of marketplace reactions to AI art applications. The mean rating score for all sample is 4.06 which reveals the positive evaluations regarding the AI art apps in the marketplace. PixAI: Anime Art Generator, CreArt : AI Art Generator and Photoleap: Photo Editor / AI art are the top rated mobile apps in the sample, while Anime AI Art - Otaiku, Remix: AI Image Creator and Wonder - AI Art Generator are the apps with lowest rating scores.

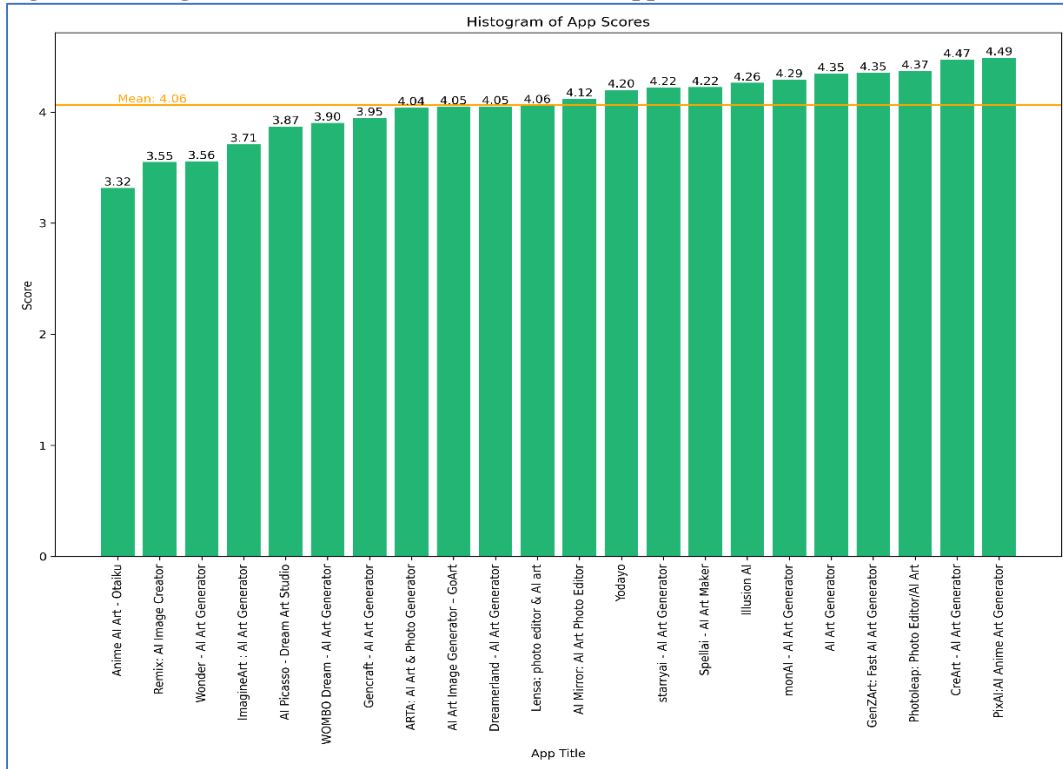**Figure 2: Rating Score Distribution of AI Art Mobile Apps**

Figure 3 combines the perspectives of previous figures with a heatmap figure of rating scores by genre information. It indicates that photography category applications tend to be higher/equal to mean rating score of sample, while the arts & design category has volatility among the applications. It can be concluded that the more detailed evaluation of users' feedback in this volatility may helpful to understanding of the consumers.

Figure 3: Rating Score Heatmap for Categories
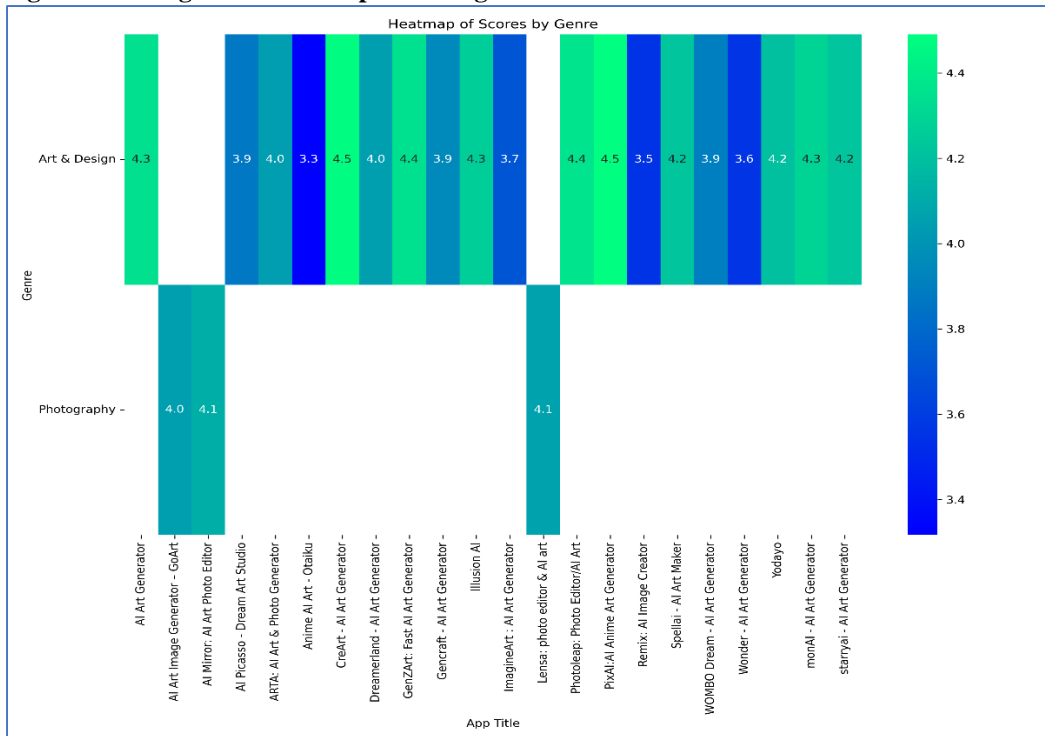
The install / download numbers are indicators of popularity in the mobile apps market and Google Play Store classifies the application install amounts into groups like 50.000+, 100.000+, 500.000+, 1.000.000+,

5.000.000+, 10.000.000+. Figure 4 highlights that majority of AI art mobile apps have been installed less than 5.000.000+ times which indicates the relatively early stage of adoption for this category. Only six of twenty two applications have more than 5.000.000+ install amounts which also indicates the potential of the AI art mobile apps.

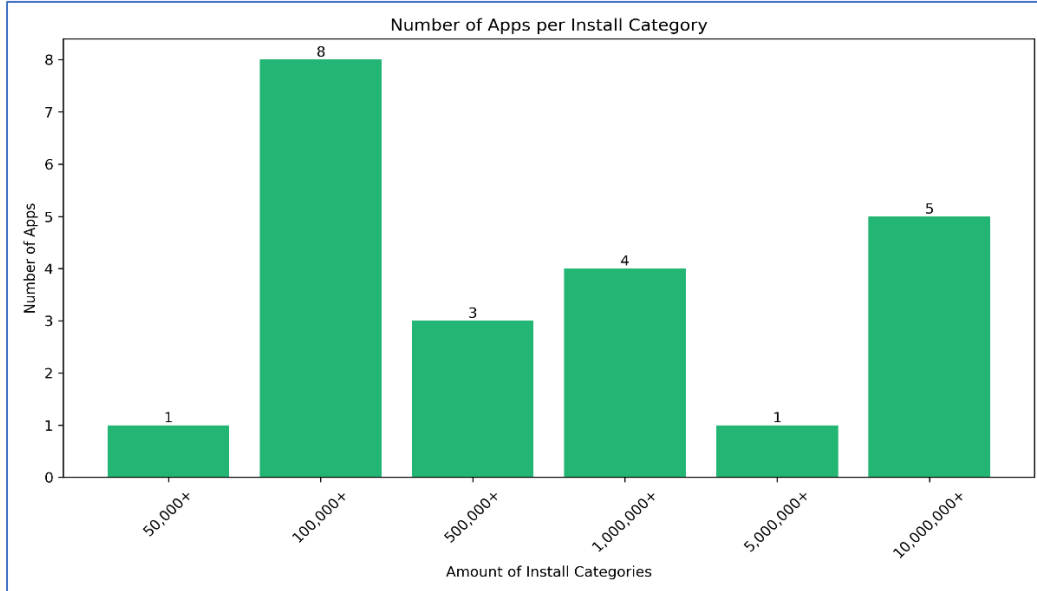**Figure 4: Install Amount Distribution**

Figure 5 extends the Figure 4's explanation to a detailed level of average rating scores for each install amount levels. It shows that most popular AI art apps have mean rating scores below 4.0, while the mobile apps with 50.000+, 100.000+, 1.000.000+ and 5.000.000+ install amounts have more than 4.0 mean rating scores. The evolution of install amount with rating scores can helpful for better understanding the consumer attitudes.

Figure 5: Boxplot for App Scores and Install Amount
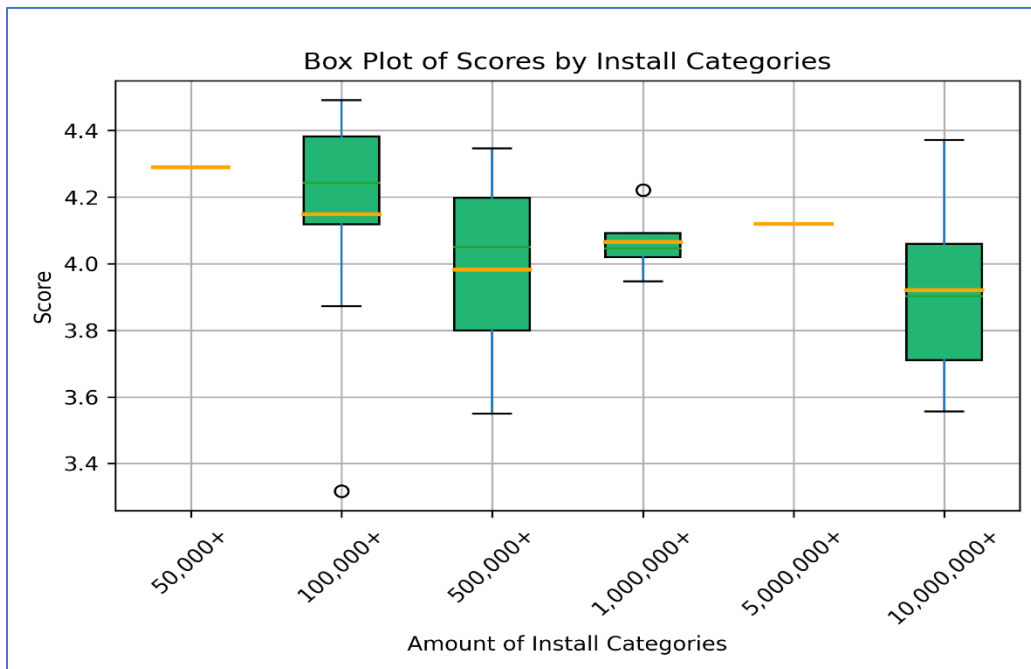
The last stage of research approach employs topic modelling methodology and BerTopic (Grootendorst, 2022) model for discovering the topics. The text section of user reviews are used for topic modelling and the study identifies 87 dispersed topics and the top ten topics are concluded in the Table 2. The volume of occurrence of eact topic and ten words associated to each topic are presented in Table 2. Following the overvall meaning of

associated words, the topics are named.The top topics detected in the study are "dissatisfaction about amount of advertisements in app" (522), "NSWF content and moderation" (313), "praise of application" (196), "functionality problems & crashes" (169), "payment necessity and trial problems" (157), "in-app purchase restoration problems" (139), "specific feature in app" (137), "chat function" (105), "credit system" (103)" and "excess of ads" (103).

The first part of topic modelling presents the topics structure overal, however, evaluation of each topic with representative reviews highlights better insights about the consumer feedback. Table 3 clarifies the topics included in conversation with the representative reviews.

Table 2: Topic Modelling Results

Topic Name	N	Words								
Dissatisfaction about amount of advertisements in app	532	ads	ad	watch	you	to	the	an	it	app	but
NSFW content and moderation	313	nsfw	words	content	inappropriate	censorship	now	word	the	that	app
Praise of Application	196	app	love	easy	very	this	great	good	nice	awesome	amazing
Functionality Problems & Crashes	169	app	it	crashes	this	and	update	work	crashing	is	the
Payment Necessity and Trial Problems	157	pay	free	you	photos	trial	to	then	pictures	images	for
In-App Purchase Restoration Problems	139	restore	lifetime	phone	new	button	support	purchase	my	paid	account
Specific Feature in App	137	avatar	avatars	magic	paid	photos	the	for	me	subscription	money
Chat Function	105	chat	tavern	bot	bots	beans	ai	chatting	chats	the	character
Credit System	103	credits	credit	daily	free	to	but	day	had	get	only
Excess of Ads	103	ads	ai	ad	watch	art	the	an	to	you	and

Table 3: Representative Reviews for Topics

Topic	Review
Dissatisfaction about amount of advertisements in app	"This app is terrible. They make you watch a 30-second ad before you can create something & it's so buggy that after you've sat through it, you click the X to close the ad & it either takes you to the ad's link or goes back to the creation page & makes you watch another ad, then another, then another, etc. Sometimes it works & you get to actually create something, but more often than not, it just puts you in an endless loop of advertising. Bleh... uninstalling it now."
NSFW content and moderation	"I was liking the original and had promise for pro but you have a NSFW slider now that means nothing if every time you try and make something NSFW it just gets labeled as inappropriate and you aren't allowed to use any words that would make it NSFW like you used to"
Praise of Application	"Very nice app love it, and easy to use"

Table 3 continued

Functionality Problems & Crashes	"At first this app was working great, but after a while I kept experiencing problem after problem. Every time I tried to use it, the ads would often kick me out of the app and I would have to start over again. Other times it would freeze and I would have to restart my phone. I tried my other apps and they work just fine so I know it's this app. I'm tired of it. This is not worth the download if all it does is prevent you from using it in the first place."
Payment Necessity and Trial Problems	"Got the free trial and the magic photos thing. Paid for the photos, but the app glitched and didn't give me the photos and doesn't show the free trial even though the money has been taken out of my account. I have a Google Play receipt for it too. My account is connected to my Gmail also and it doesn't show that I have the free trial in the app, even though Google Play says I do. Very frustrating. Definitely would like my money back!"
In-App Purchase Restoration Problems	"ZERO STARS I upgraded my phone and tried to restore my lifetime purchase on my new phone and it didn't work. I tried emailing them to restore my purchase or give my money back and I get an automated email walking me through the restore process that doesn't work... EVERY TIME I try to email them. There's no one to contact and I lost my purchase of this app. RIP OFF! DO NOT DOWNLOAD!"
Specific Feature in App	"You are required to sign up for a subscription plan that limits you to 3 photo "upgrades" per day but you have to pay extra ($7.99+) for the Magic Avatars, which is what I wanted to use the app for. I imported my photos and paid as prompted for the Avatar feature, after which it said it was applying or processing the effects, only to take me me right back to the pay screen with an error. Of course, I was charged for it but I have nothing to show for my purchase (2x), and keep getting errors."
Chat Function	"The art is amazing, the chat bot is also amazing. I get so many good images with good quality. The responses of the chat bots are also perfect. I just would like to see the character settings of other chat bots, or else This app is absolute best ai generator and chatting app."
Credit System	"They used to give you 5 free daily (per 24 hrs) credits to make creations with options to earn more credits in various ways. You can watch a few seconds of an ad to get 2 credits, but there not much you can do with that. And now, for whatever reason, it says to come back at 5 a.m. to get my 5 credits. I haven't used the app in weeks, so the credits should have been reset to whenever i open the app. They want a minimum of $11 to get the minimum credit offering. Terrible, imo."
Excess of Ads	"Ad after ad after ad, I tried to create my first Ai art and I had to watch two ads and then when I finally saw it I wanted to recreate it and again another ad, this is very frustrating as it takes away from the app, all these ads will become more frequent and irritating just so you buy the subscription which is not right, it shouldn't bully you with ads to buy something."

First topic -Dissatisfaction about amount of advertisements in app- has significant number of occurrence in the reviews (N=532) and common terms such as "ads", "ad", "watch" represents the frustration about the frequency apps which leads to a conclusion of negative impact to user experience for AI art app category. The second topic -NSFW content and moderation- has 313 occurrence and common some common terms such as "NSFW", "inappropriate" and "censorship" are signaling this topic and user reactions. Despite the criticism in the top topic, the third topic -Praise of application- indicates the positivity of user reviews in AI art apps. Common terms such as "love", "easy", "awesome" represents the positivity of market towards the AI art applications.

Following the most occurred topics examination, the content scope of the topics can be examined through specific/generic perspective. Topics like "Functionality Problems & Crashes", "Praise of Application" and "Excess of Ads" have the commonality with the other types of mobile applications in the literature, since these topics are common themes for majority of mobile app categories. On the other hand, specific themes can be associated with the AI art mobile applications. For example, one user indicates in "Specific Feature" category as *"you are required to sign up for a subscription plan that limits you to 3 photo "upgrades" per day but you have to pay extra ($7.99+) for the Magic Avatars, which is what I wanted to use the app for. I imported my photos and paid as prompted for the Avatar feature..."*. In another category -credit system-, user talks about credit systems included in AI art mobile apps as *"They used to give you 5 free daily (per 24 hrs) credits to make creations with options to earn more credits in various ways. You can watch a few seconds of an ad to get 2 credits, but there not much you can do with that..."*.

5. Conclusion

The study sets out to examine AI art mobile applications as a novel context in mobile application area and the aim of the study is evaluating the user reviews and the topics included in conversation. 8159 user reviews from 22 mobile applications are examined with topic modelling approach in the study and top ten topics are presented in the study.

In the first part of the results which uses descriptive findings, the overall aspect of market through rating scores are examined. It is concluded that AI art mobile applications are perceived positively (by rating scores) and the category has potential for the future (by install amounts). The second part of the study employs topic modelling to understand the user reviews by text content. The concluded topics are "Dissatisfaction About Amount of Advertisements in app", "NSFW Content and Moderation", "Praise of Application", "Functionality Problems & Crashes", "Payment Necessity and Trial Problems", "In-App Purchase Restoration Problems", "Specific Feature in App", "Chat Function", "Credit System" and "Excess of Ads".

The concluded topics signals the polarities as positive and negativity sides. For the positive side, "Praise of Application" is the most significant topic found in the study. For the negative side, "Dissatisfaction about amount of advertisements in app", "Functionality Problems & Crashes", "Payment Necessity and Trial Problems", "In-App Purchase Restoration Problems" are the topics concluded in the study. In addition to polarity side of topics, the content side of topics are also helpful. The finding of this part has common results with the literature as the topics of "Functionality Problems & Crashes", "Praise of Application" and "Excess of Ads" are already concluded in other studies. However, this study contributes to theory of AI art by presenting the specific topics like "Credit System", "Payment Necessity and Trial Problems", "NSFW content and moderation".

For the practical side of the study results, the main idea of evaluating the market with the study's perspective is examining the overall situation of market. In addition, evaluation of specific topics and expressed ideas/opinions in those topics can be used for competitive decision-making, since it can signal the strengths and weaknesses of AI art mobile applications. They can be either used for detecting the pro's and con's of company's mobile applications or discovering the complaints regarding the competitor's mobile applications. For the future of practical side of generative AI, the concept poses significant potential for companies in various industries. For example, Goldman Sachs (2023) research estimates that generative AI software market may have $150 billion total addressable market. Developing generative AI-enabled products for final users require understanding the marketplace and product development, therefore it is critical to understand the examine the concept by several aspects such as economical value, design principles (Weisz et al., 2023) and so on. Future studies in generative AI area can utilize market-based, product-based and consumer-based perspectives.

For the theoretical side of generative AI; extension of the study sample into other markets such as Europe, Asia and other countries can be helpful for contextual richness in literature. As the different markets contain various languages, cultural effects and differences regarding languages can signal potential research directions. For the methodological side for the future studies, additional methodologies such as sentiment analysis can be helpful to better understanding the market feedback. Sentiment analysis including several emotion categories can enrich the polarity-based approaches which employs positive-negative-neutral polarities and examination of specific emotion categories in AI art mobile app reviews can be helpful.

Contribution Rate Declaration

The author's contribution rate is 100%.

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