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ÇEVRİMİÇİ DEĞERLENDİRMELERDE DUYGULARIN HARİTALANMASI: MOBİL UYGULAMALARA İLİŞKİN KULLANICI YORUMLARINDA DUYGU YELPAZESİNİN İNCELENMESİ

MAPPING THE ONLINE REVIEWS SENTIMENT LANDSCAPE: AN EXPLORATION OF EMOTION SPECTRUM IN USER REVIEWS OF MOBILE APPS

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ÖZ

Mobil uygulamalar, tüketiciler için güçlü platformlar olarak ortaya çıkmıştır ve mobil bağlamda kullanıcıların içerik ve duygusal yönlerine göre tutum ve tepkilerini anlamak, pazarlama karar verme sürecinde hayati önem taşımaktadır. Kapsamlı bir yaklaşıma sahip olan çalışma, belirli duyguları (öfke, tiksinti, korku, sevinç, nötr, üzüntü, şaşkınlık) inceleyerek mobil uygulamalardaki kullanıcı yorumları bağlamındaki duygu spektrumunu analiz etmeyi amaçlamaktadır. Duygu analizi metodolojisi ("Emotion English DistilRoBERTa-base" transformatör modeli aracılığıyla), 34 mobil uygulama kategorisinden 302.647 incelemeden oluşan veri kümesinde kullanılmıştır. Duyguların kategorik olarak incelenmesinde en baskın duygu kategorisinin tarafsızlık olduğu, bunu sevinç, üzüntü, tiksinme, şaşkınlık ve öfke duygu kategorilerinin takip ettiği, en az baskın olan kategorinin ise korku kategorisi olduğu görülmektedir. Polarite incelemesine göre; olumsuz kutupluk incelemeleri nötr, üzüntü ve tiksinme duygularıyla ilişkilidir; nötr kutupluk incelemeleri tarafsızlık ve üzüntüyle ilişkilendirilir; Olumlu kutupluluk incelemeleri, nötr ve sevinçli duygu kategorileriyle ilişkilidir. Analizin son kısmı duyguların tek tek incelenmesini ve her bir duygunun baskınlık sıklığı en yüksek olduğu mobil uygulama kategorilerinin sunulmasını içermektedir. Duyguların dağılım oranları ve farklı uygulama kategorileriyle duyguların bireysel ilişkileri gelecekteki akademik araştırmalara ve pazarlama karar alma süreçlerine ışık tutar.

ABSTRACT

Mobile applications have emerged as powerful platforms for consumers and understanding the attitudes and reactions of users by content and emotional sides in a mobile context becomes crucial for marketing decision-making. The study with comprehensive approach aims to analyze the emotion spectrum in mobile applications user reviews context by examining specific emotions (anger, disgust, fear, joy, neutral, sadness, surprise). Sentiment analysis methodology (through "Emotion English DistilRoBERTa-base" transformers-model) is employed on the dataset of 302.647 reviews from 34 mobile application categories. Categorical examination of emotions indicates that neutrality is the dominant emotion category, followed by joy, sadness, disgust, surprise, and anger emotion categories, while the fear category is the least dominant category. According to polarity examination; negative polarity reviews are associated with neutral, sadness and disgust emotions; neutral polarity reviews are associated with neutral and sadness; positive polarity reviews are associated with neutral and joy emotion categories. Final part of analysis includes examination of emotions individually and mobile app categories which each emotion with the highest frequency of dominance are presented. The distribution rates of emotions and the individual relationships of emotions with different application categories can shed light on future academic research and marketing decision-making.

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Introduction

Today's consumers spend their time online and according to We Are Social & Meltwater's (2024) Digital 2024 Report, the average amount of time spent using the internet was 6 hours 40 minutes in 2023 Q3. One of the most crucial advances of the digital world regarding consumers and markets is the increase in the amount and speed of information and experience feedback that consumers and businesses transfer to each other within the market. Today's consumers can directly convey their positive/negative experiences about products or services to companies or other users through various platforms. On the experiences side, mobile applications and mobile experiences have become essential to today's consumer's daily life and consumer experiences. Different categories of applications and the resulting ecosystem that appeal to different user habits have become an important research area for businesses and consumers. Two realities combined lead to the necessity of understanding today's consumers' feedback about the applications they spend time on, which becomes valuable for the mobile application market.

Mobile applications consumed by larger audiences in the market are one of the important parts of today's mobile world. While mobile application types and usage purposes are becoming richer day by day, mobile applications in various fields such as finance, fitness, health, and travel accompany consumers' daily lives. On the other hand, with the development of technology, new contexts emerge, and diversity increases. Previous studies in the literature focuses on several concepts such as sales of mobile apps (Liang et al., 2015), continued use (Lee, 2018) and dissatisfaction (Sally, 2023). The content side of online reviews are already examined in literature by topic side (Permana et al., 2020) and emotion side (Mondal et al., 2024) already. However, previous studies has limited contexts and a comprehensive and integrated approach for the content and emotion is required to understand the landscape of the mobile application ecosystem. This study focuses on the research gap about the comprehensivity of ecosystem by utilizing various mobile application categories with a larger dataset.

Business can make use of consumers' writings about products in a category for better understanding of marketing opportunities, competitive landscape, market structure and features of products either their own products or competitors (Netzer et al., 2012). This study starts from this idea and set outs to examine the online review ecosystem by emotion perspective. The research questions/topics are related to several aspects of the study including; i) the current state of emotions in the conversation, ii) emotion spectrum among mobile applications category, iii) polarity and granularity in online reviews emotions, iv) individual emotion analysis. Consistent to research topics, sentiment analysis methodology including eight emotion category is employed for the dataset of 302.647 online reviews. The study starts with literature review sections of eWom and emotions and continues with the methodology part which leads to discussion and conclusion sections. The study sets out to conclude a comprehensive understanding of the emotional spectrum that guides mobile marketing decision-makers about emotions and mobile app categories from a consumer perspective.

Literature Review

eWom and Online Reviews

Westbrook (1987) defines word of mouth concept as *"informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers"*. The technology and social media enabled the growing impact of the concept to the larger audiences around the world and the concept has been extended into electronic format as eWOM. eWom is defined as *"all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers"* (Litvin et al., 2008). eWOM source have crucial role in consumer decision-making (Jalilvand et al., 2011), people are affected by it either in positive or negative ways (Hussain et al., 2018) and it becomes an enduring part of online marketing mix (Cheung et al., 2008). The business and marketing decision-makers assess the marketing environment by scanning the online channels and get feedbacks about their products and services.

eWOM concept contains various components and content forms in online environment. Previous studies employs the variety of forms such as tweets (Jansen et al., 2009; Alboqami et al., 2015), facebook posts (Liu et al., 2017), blogs (Kozinets et al., 2010). Online reviews defined as *"peer-generated product evaluations posted on company or third party websites"* (Mudambi & Schuff, 2010), is one of the popular content form in eWOM and contains text-based data, rating scores and additional data types. Since the product experiences on internet forums are judged as trustworthy (Bickart & Schindler, 2001), assessing which components inside the eWOM content by their effectiveness and impacts to the audiences is one of the essential task in digital marketing.

The content side of the online reviews is related to the functions and components of the reviews. For the functions side; according to Park et al. (2007), online review has a dual role; one for informant role that provides product information in a user-oriented way, and one for the recommender role that includes recommendations of previous customers in eWOM format. These roles can be included in online reviews either in singular form or hybrid forms. For the component side; online review websites provides various formats and types of content that users can use for presenting their opinions. The component can either include only-text content, rating scores and text reviews or text and images together. The task of marketing decision-makers refers to examining the content with motivations and consumer psychology since the users reflect their inner state and experiences together in online reviews.

Understanding emotions in user reviews, where users can convey their experiences, thoughts, and feelings, is essential for marketing decision-makers. As the expressions of feelings are leading to higher satisfaction and better product evaluations (Nyer, 2000), evaluating the different aspects of emotions such as rage (McColl-Kennedy et al., 2009), love (Kim et al., 2010), hate (Zhang & Laroche, 2020) and anxiety (Khoa & Huynh, 2022) will be helpful to market assessment. Grasping users' emotions in user reviews will contribute to a better understanding of the market and the development of products/services.

Emotions in Online Reviews

Customers transfer their experience, knowledge and emotions through the user reviews to the other users. The emotion side can be in form of polarity (positive / negative) or in the form of the specific type of sentiments (fear, anger, joy). Theoretically, emotions is defined as *"organized psychophysiological reactions to news about ongoing relationships with the environment."* (Lazaruz, 1991). In online context, news may refer to the experience of using the product/services and reactions may be reflected into the online reviews. Assessing the emotions in online review context has been studied with several contexts including; purchase intention (Guo et al., 2020), perceived usefulness (Felbermayr & Nanopoulos, 2016), emotional contagion (Herrando et al., 2022). The variety of the consequences and related concepts for emotions transfer require assessment of emotions in online review content.

Emotion analysis for online reviews basically depends on methodology called as sentiment analysis. Basically sentiment analysis is *"the computational study of people's opinions, attitudes and emotions toward an entity"*. (Medhat et al., 2014). According to Bhadane et al. (2015) it is an NLP (Natural Language Processing) area and deals with identification of mood / opinion regarding the subjective expressions in the text. Customers express their emotions in the text content implicitly and processing the text can lead to extraction of the sentiments within the content. The extraction of the sentiments have two main approaches; the first one focuses on detecting the polarity in the content and extracts positive / negative / neutral emotions, while the latter one assess the emotions in detailed way and extracts specific sentiments within the content.

The first approach simply refers to valence in online review and it is about whether the emotion in the content is predominantly positive or negative (Purnawirawan et al., 2015). It can be indicated by average rating (Langan et al., 2017) and it represents the polarity in online review. The advantage of using valence concept in online reviews refers to assessing the overall tendency of the users/market, however, the valence concept does not provide the detailed examination which is required for consumer behavior researches. The second approach focuses on this detailed examination and relies on the several sentiments that can be extracted from online reviews. In his classical study, Plutchik (2001) identifies eight primary emotions as anticipation, anger, disgust, sadness, surprise, fear, trust and joy. According to other classic view, Ekman (1992) mentions the universal signals for the emotions such as anger, fear, enjoyment, sadness and disgust in his study. Valence-based approaches can simplify the process by classifying the polarities, multi-emotion sentiment approaches can signal the components or varieties in the emotions.

Evaluating the sentiment polarities and emotions variety in online reviews contributes to marketing decision-making. As Bai (2011) implies in her research, precise methods of predicting sentiments provides lots of advantages to companies from assessing online customers' preferences, having strategic advantage to detecting cyber risk and security threats. According to Yang et al. (2020), evaluating customer sentiment tendencies can helpful in improving service quality and consumer satisfaction for the businesses on e-commerce platforms. The next section focuses on customer emotions topic in the mobile applications context by employing sentiment analysis to understand the consumers' emotions in mobile application market.

Methodology

Research Approach

Sentiment analysis as a tool for understanding the content side of user reviews is one of the helpful methodologies in consumer research. In classical lexicon-based models, existing dictionaries associated with polarities/emotions are used to identify the words included in the text. However, this approach has disadvantages about such as detecting the sarcasm or not evaluating the context. According to Naseem et al. (2021), categorical word representations have disadvantages in understanding the syntactic and semantic meaning of words. The newer approaches such as word embeddings defined as *"a feature learning method where a word from the vocabulary is mapped to N dimensional vector."* (Naseem et al., 2021) can be better for understanding the content. Language representation models use word embeddings approach for better understanding the context and the content and this study follows this approach for improving the understanding of sentiment in user reviews.

Data Collection and Sample

The study employs Python programming language (Van Rossum & Drake,1995) and google-play-scraper (Mingyu, 2024) module to retrieve the data in the Google Play Store. Sampling decision relies on the application categories on Sensor Tower website (Sensor Tower, 2024) and the sample of study covers all the categories in Google Play store. The sampling is employed based on 06.05.2024 data and top 25 applications of 34 categories are chosen as source. The category names are presented in Table 1. The study focuses on US market and reviews written in English. For the user reviews filtering on Google Play store, "most relevant" user reviews for the mobile applications are retrieved. Data collection takes place on 08.05.2024 and 302.679 reviews are obtained for the first stage of the analysis.

Table 1. Application Categories in the Sample

Category Names			
Art & Design	Entertainment	Lifestyle	Shopping
Auto & Vehicles	Events	Maps & Navigation	Social
Beauty	Family	Medical	Sports
Books & Reference	Finance	Music & Audio	Tools
Business	Food & Drink	News & Magazines	Travel & Local
Comics	Games	Parenting	Video Players & Editors
Communication	Health & Fitness	Personalization	Weather
Dating	House & Home	Photography	
Education	Libraries & Demo	Productivity	

Sentiment Analysis

For the emotion side of the user reviews, the study focuses on sentiment granularity rather than the polarities and extracts specific emotions included in the text through transformers model. This study uses transformers-model named "Emotion English DistilRoBERTa-base" (Hartmann, 2022) and the analysis section examines the reviews with sentiment analysis and retrieve the sentiment score probabilities for each review during the analysis. The sentiment analysis outputs the probabilities of sentiments in numerical values and the highest probability regarding a sentiment is evaulated as final sentiment in the study. Mobile application users can express their emotions directly by a solid individual emotion, the probabilities indicate the clear emotion in the review. However, due to complexity of human emotions and expressions, there can be multiple emotions indicated in the review. In this scenario, the highest probability will give the final emotion in the text. For example, the first review in Table A has the joy emotion category as the final sentiment, while the second review has the anger emotion category as the final sentiment.

Table 2. Sample Sentences and Emotions Probabilities

Sentence	anger	disgust	fear	joy	neutral	sadness	suprise
I have downloaded the game, it is so funny! Happy with the characters in the game. You should add more characters!	0.008	0.006	0.001	**0.870**	0.020	0.003	0.089
I like the application at first. I mean, it was so cool, seems promising. However, i had started to have problems with some functions. The application is frustrating me everytime i try to use specific feature!	**0.333**	0.037	0.002	0.311	0.090	0.148	0.076

Transformers-model has limitations about tokens, that are the parts of the texts that can the language models can process. Some user reviews in the sample set exceeds the limit and they are excluded from the sample, since the examining the sentiments in two or more parts may have the detection problems about the integrity of the sentiment in online review. 32 reviews are excluded from the sample and sentiment analysis is employed for 302.647 reviews as the final sample.

Results

The results of the data analysis have three main sections that can be associated with evaluation approaches in a deductive perspective. For the first section, sentiments included within the conversation are examined in a basic level, then the emotion spectrum among categories are examined for an overall review, it is followed by evaluation the polarity of rating scores (negative, neutral and positive), finally emotion categories are evaluated individually to have better insights.

Emotion Correlation Analysis

In the first step, relationships between emotions are crucial for starting part of analysis. Figure 1. shows the correlations of the sentiment possibilities in the sample set.

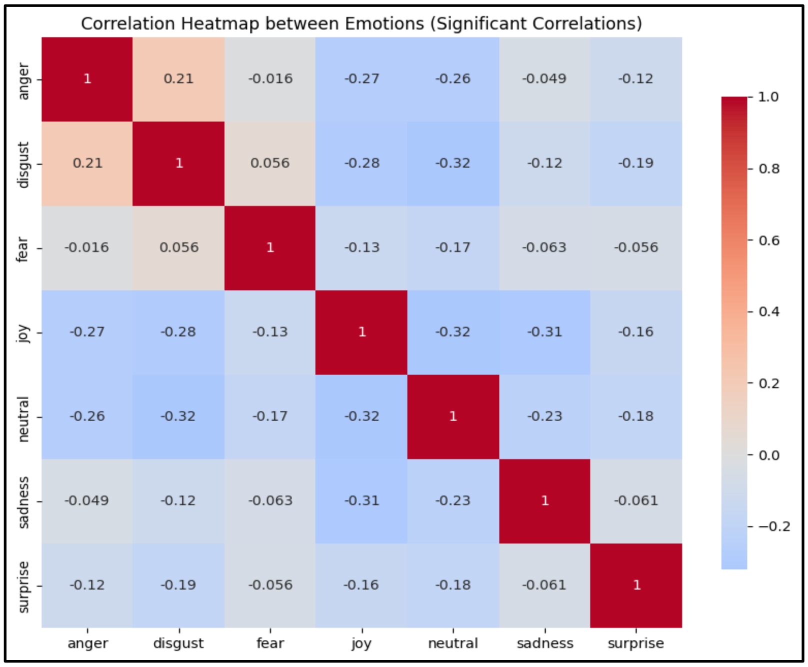

Figure 1. Sentiment Correlations Heatmap

Figure 1 depicts that anger and disgust emotions have the highest positive correlations (21%), It can be concluded that when users express the anger/disgust emotion in the user reviews, they tend to express the second emotion as well. The second finding in figure reveals that joy and neutral emotions pair (-32%), disgust and neutral pair (-32%) and sadness and joy pair (-31%) have highest negative correlations. Therefore, it can be concluded that when the neutrality becomes active in the user reviews, joy and disgust type emotions are decreasing. This can signal the extremity side of joy and disgust emotions. Sadness and joy are can also be evaluated as the opposite emotions in the dataset. Finally, it can be depicted that anger and disgust has a correlation relationship, while joy and neutral emotions have distinct characteristics in the dataset.

Emotion Spectrum in Categories

The second part of the analysis focuses on the dataset by a comprehensive approach and focuses on the final emotions detected in dataset, rather than the possibilities. Figure 2 shows the distribution of all emotion categories among the categories.

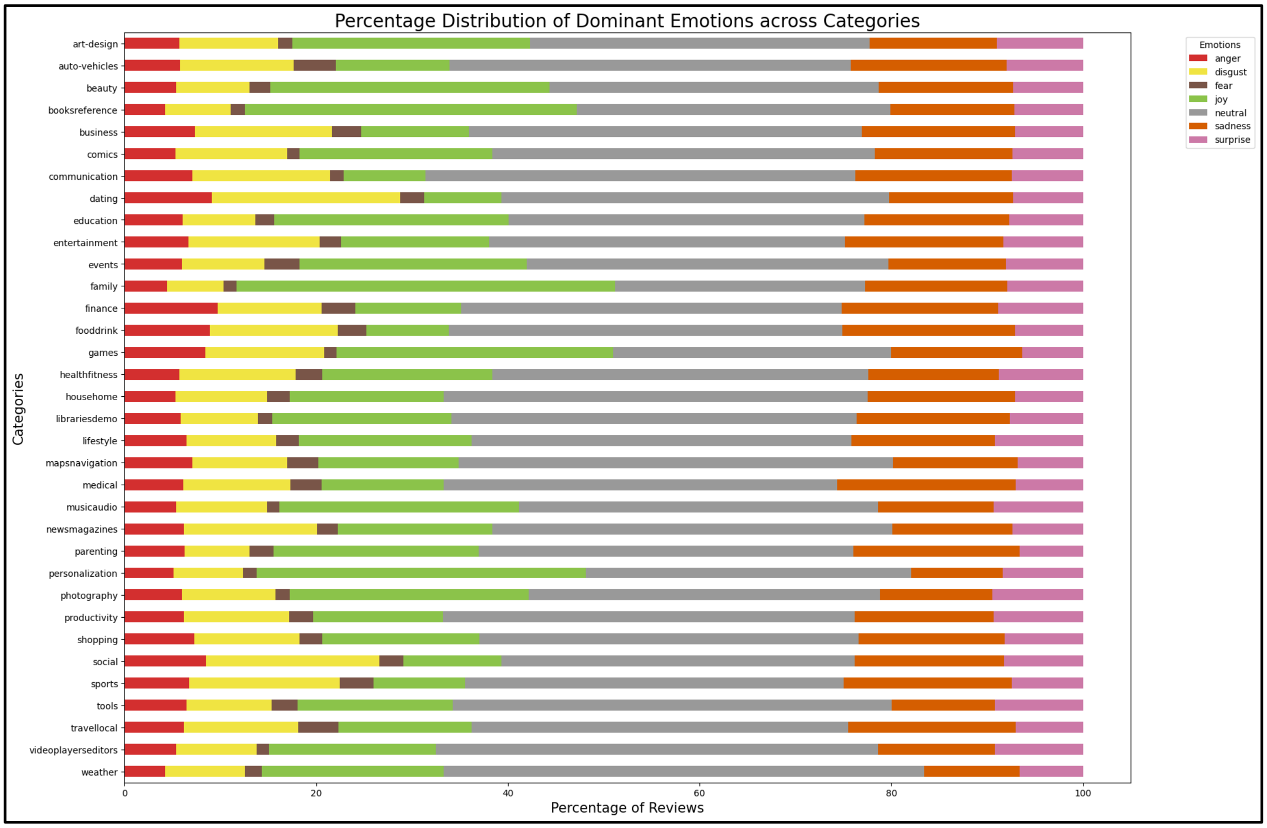

Figure 2. Sentiment Spectrum Across Categories

Figure 2 findings have four main implication areas for sentiment spectrum;

1- the dominance of neutrality in general,

2- varying levels of anger, disgust, joy and sadness

3- Identical levels of surprise

4- the minority of fear among categories

The dominance of neutrality

User reviews have specific emotions inside the content which lead to specific emotions and they also have some neutral emotions which has a neutrality toward the application or it can be related to combining of different emotions included. This neutrality phenomenon takes place for each mobile application category and it reflects the fundamental expression pattern of user reviews across categories.

Varying levels of emotions

Varying levels of emotions are detected for different categories in the sample as consistent to research aim which is about focusing the variety. Differences between levels of anger, disgust, joy and sadness reveal that different type of emotions related to specific categories include valuable insights about specific contexts. For example; Figure 2 shows that family category has one of the highest joy emotion percentage (indicated as green bar proportion) which can be signal for evaluating the further side of the family mobile application category for the scientific research. Figure 6-12 examines the emotion categories and top categories associated to each emotion in more detail.

Identical levels of surprise emotion

The figure reveals the identical levels for surprise emotion. There are two possible reasons for this finding; it can be associated to the dominant sentiment aspect in the analysis which indicates that surprise is not the dominant sentiments within the review, or it can be associated to the user behavior related to writing the things they experienced already which does not have so much surprising element or they do no tend to include this emotion.

The minority of fear emotion

The figure indicates that fear emotion is the least popular dominant emotion across the categories. Users tend to mention about other emotions more than fear in the reviews. However, it also signals a potential research area since even it has low proportion in the dataset, detecting the sub-components of fear can be potential research areas in mobile research.

Polarity and Granularity Integration

In the third stage of findings, the reviews are organized into three categories as negative reviews (rating scores of reviews are 1 or 2), neutral reviews (rating scores of reviews are 3) and positive reviews (rating scores of reviews are 4 or 5). This type of classification enables the examination of polarity of ratings with the sentiment granularity employed in the analysis of the study. The integration of polarity and granularity helps to evaluate the emotion spectrum in a more detailed view.

The first figure in this section, Figure 3 presents the distribution of emotion categories in negative type of reviews. It starts with the most popular emotions as neutral category which is common emotion across the dataset. The following emotion categories signal the structure of granularity in negative reviews. The first one "sadness" category has the 22.1% of the negative reviews, while the next one "disgust" and the following one "anger" have 19.8% and 10.9% of the negative reviews. They indicate that when users are writing negative reviews by rating scores of 1 and 2, they expressed sadness, disgust and anger to application reviews.

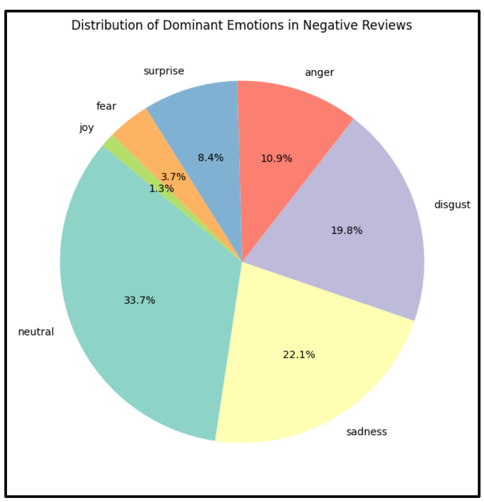

Figure 3. Negative Reviews Sentiment Spectrum

The second category as neutral reviews (rating score = 3) has the highest proportion as neutral emotions as expected. However, the following categories that are prominent in neutral reviews also have potential for better understanding of users. It is found that 18.3% as sadness category, 8.1% as disgust category, 7.6% as surprise category and 7.3% as joy category. The "secondary" emotions in the neutral polarity indicates the emotional diversity of neutral reviews in the conversation.

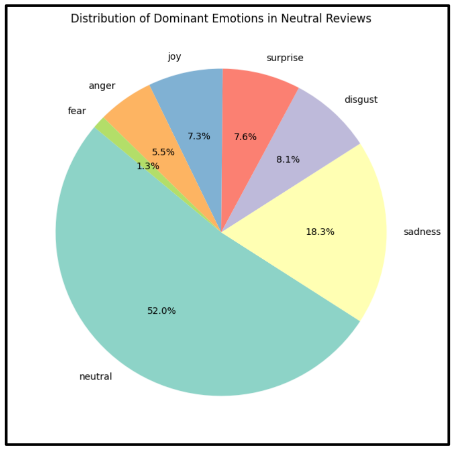

Figure 4. Neutral Reviews Sentiment Spectrum

The third category as positive reviews (rating score is 4 or 5) includes neutral emotion and joy emotions as the highest proportions. 42.5% of joy emotion category indicates the singularity of expressions in terms of emotion diversity in the user reviews. Comparing to negative and neutral polarity categories, positive category has more solid emotion structure in terms of 42.1% and 42.0% proportions.

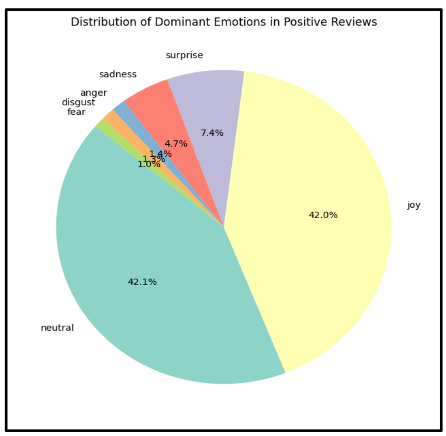

Figure 5. Positive Reviews Sentiment Spectrum

The integrated analysis of polarity and granularity approaches signals the main structures of the emotion distributions in the polarity categories. However, each emotion category has specific characteristics that require detailed evaluation. The next analysis section focuses on the emotion categories individually by examining them with the mobile application categories.

Emotions Analysis by Categories

Section 4.2 provides the emotion spectrum among the categories and presents the overview of emotion spectrum, while section 4.3 examines the rating score polarities with the emotions. These two sections provide a solid background for the emotion spectrum analysis, however further examination is needed, since each emotion can be associated with various conditions. Section 4.4 highlights the emotion categories with most associated mobile application categories and includes the top 5 user reviews in each emotion category to better understanding of emotions.

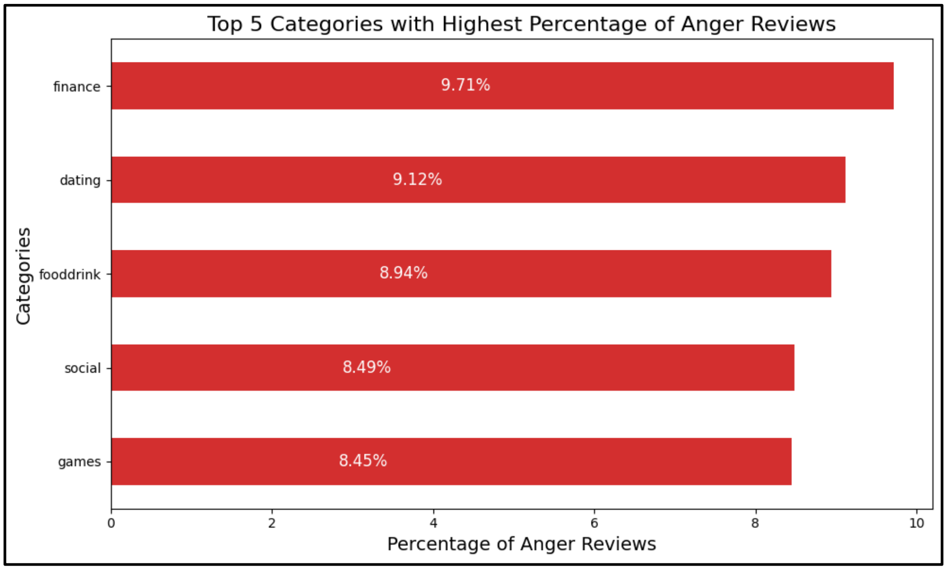

Figure 6. Anger Emotion and Top Categories

The first category - anger - has the most percentages of finance (9.71%) , dating (9.12%), food & drink (8.94%), social (8.49%) and games (8.45%) categories. The anger emotion category is not one of the frequent emotion category included within application categories. However; with the "direct" expression nature, it can help mobile application developers to negativity side of user feedbacks with the intense feedbacks. Table 3 conveys sample reviews with the highest probabilities that represents the emotion category.

Table 3. Anger Emotion Sample Reviews

User Review	Prob.	Category
i request for my money back which i was charged without my knowledge. i downloaded this app, last year perhaps and deleted it without using much of it,. today $90 comes out of my account without any notification and no trace of app on my phone. ridiculous and unethical. I'm furious.	0,994676	education
Firstly it was good but when i started to play in battle i was always loosing . HOWEVER i thought it will stop after i will buy the special bundle spending all of the coins . I still loose . I was not angry at first but after attempting for more than 15 times it shows me i loose that make me really furious 😟	0,993724	games
It is a very good app, the ads are too much,it makes me delete and redownload again and even doing that, the song is not going to play,and if it makes me angrier, I am going to delete it	0,993592	musicaudio
it just gives the wall paper and everytime i swipe theres ads this is making me furious 😒	0,992279	personalization
Somebody contact me, I want to delete my account but can't, I want to speak to somebody through the app, but I can't, I am not paying that much a month when the app doesn't even work, I'm fuming and somebody needs to contact me and or delete my account ASAP! Thanks	0,991484	beauty

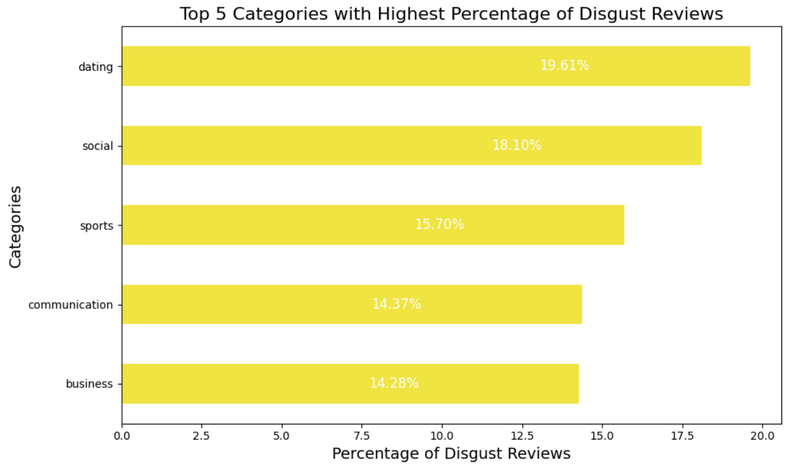

Figure 7. Disgust Emotion and Top Categories

The second category - disgust - is mostly included in the dating (19.61%), social (18.10%), sports (15.70%), communication (14.37%) and business (14.28%) categories. Unlike the anger category, disgust category is more dominant in the these categories. As the 19.61% of user reviews in dating category indicates 1 of 5 reviews apprx. is included in this category. These rations signal the necessity of examining emotion/category pairs for better understanding of user reviews. Table 4 presents the user reviews with top probabilities in the disgust emotion category.

Table 4. Disgust Emotion Sample Reviews

User Review	Prob.	Category
Thought I would try it. Everything is 100% polyester and smwlls so bad. Tried returning products but it was so much of a headache I gave up. Absolutely unsatisfied and disgusted.	0,991507	shopping
If there was a way to outright buy it I would. Hiding 99% of the app behind a monthly subscription is disgusting and shame on the developer.	0,991478	family
If I could give this app a zero, I would. The amount of naked or near-naked people showing off their goods is appalling. When I first used this app, it was great...nothing but wholesome family content. Now however, it is beyond disgusting. I will never use this app again and neither will my kids. The developers should be ashamed for allowing a colossal amount of smut to mar what was once a great app.	0,990819	social
I really like this app, it's fun to play. However I am disgusted by the adds it's giving me to the point that I rather uninstall the app and not play anymore. This is how they get kids hooked on porn, by giving this kind of disgusting adds. It was fun until the very suggestive adda started to pop up, I truly didn't mind the adds in between the levels but I got fed up with disgusting suggestive, highly sexual adds, imagine if a kid was playing this game. Thanks but no thanks.	0,990359	games
Geniuely worst manga app i have ever used. The coin system is actually disgusting. You would spend less money buying the volume in japanese and paying someone to sit down next to you to translate or pay to have someone teach you the language. Square Enix never fails to impress.	0,99031	comics

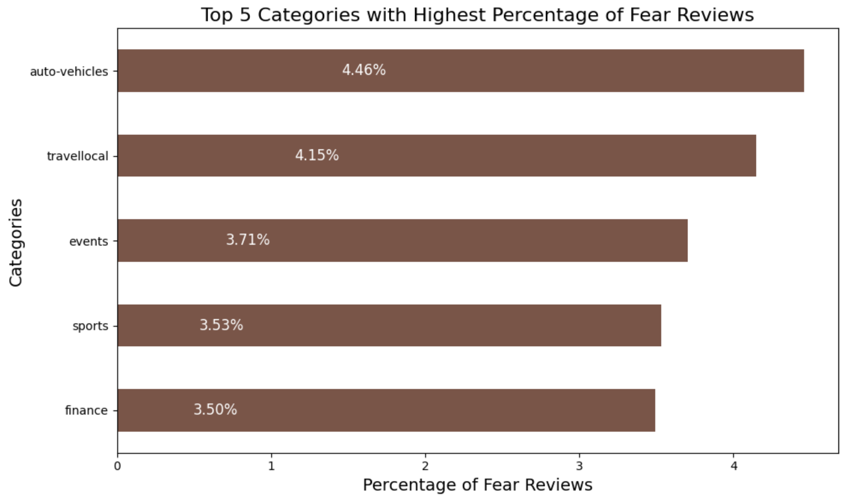

Figure 8. Fear Emotion and Top Categories

The third category - fear- is the least popular emotion category in the dominant emotions set. However, it signals more specific side of user reviews. The highest proportion for this category includes auto & vehicles (4.46%), travel & local (4.15%), events (3.71%), sports (3.53%) and finance (3.50%). Table 5 lists the user reviews with their probabilities.

Table 5. Fear Emotion Sample Reviews

User Review	Prob.	Category
it is a good idea but I felt uneasy to connect to other' people internet without their acknowledgement	0,994512	productivity
it is great dont change but how do i reset my recent emojis theres too many its making me scared 😨	0,994063	personalization
I felt that God was actually with me! I felt better and when I feel scared home alone, I just remember God and Jesus is always with me :)	0,994	booksreference
mostly negative reveiws im scared to try it. if i wanted to to make money on this i would atart with fixing it.	0,993787	librariesdemo
I love this app, I wanted to give 5 stars but I'm constantly terrorised by ads upon ads. I understand the ads are needed but maybe show just ONE ad at a time.	0,993705	videoplayerseditor s

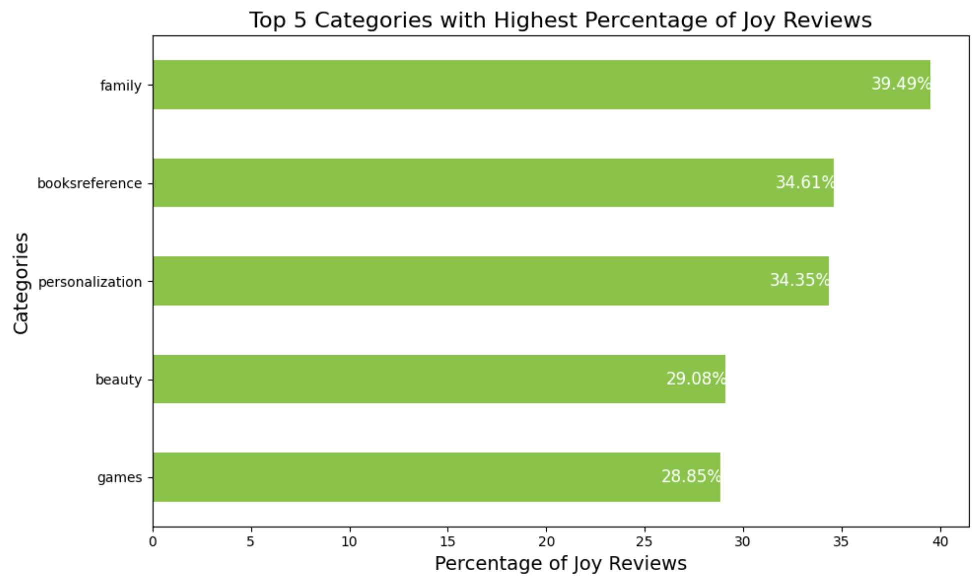

Figure 9. Joy Emotion and Top Categories

The fourth category - joy - reflects the positivity side of the user reviews and it is crucial to understand this category for evaluating the market with successful / satisfied aspects. Joy emotion is found as dominant emotion in the categories of family (39.49%), books & reference (34.61%), personalization (34.35%), beauty (29.08%) and games (28.85%). The pairs of application categories and joy emotion offers new-contexts in consumer research. Table 6 presents the sample reviews with the highest probabilities in this category.

Table 6. Joy Emotion Sample Reviews

User Review	Prob.	Category
is really fun and i want to se the people qho make the game i think the people is beautiful/handsome	0,995485	games
i like it's fun Ig	0,995249	games
I enjoy reading the scriptures every day opens my mind and heart	0,995209	booksreference
i like it is fun because I'm a kid and I'm using the talk thingy	0,995061	family
I feel good this made my day i've been having a hard time with thinking o more ideas about sports writing and this app is perfect if theres a 10 star rating i will gladly do so.	0,995038	education

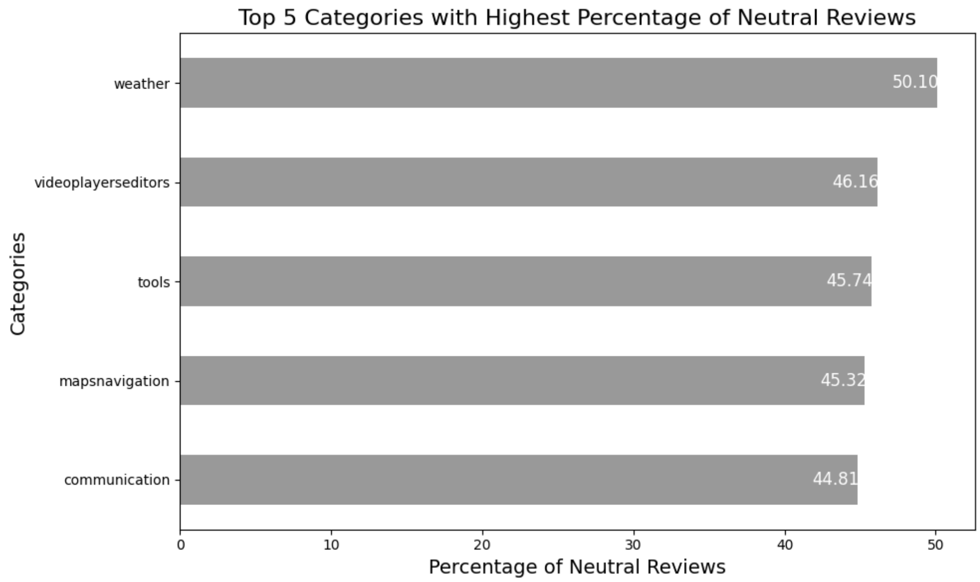

Figure 10. Neutral Emotion and Top Categories

The fifth category - neutral- does not have a direct emotion by nature. However, it is crucial to understand why users do not express the emotions or why they express emotions indirectly or complex for better understanding of users. The highest dominance of neutral emotion category in weather (50.10%), video players & editors (46.16%), tools (45.74%), maps & navitation (45.32%) and communication (44.81%) shows the utilitarian side of these categories. When users have utilitarian experiences with these specific categorizes, they write the neutral reviews rather than expression of personal emotions. Table 7 presents the sample reviews in this category.

Table 7. Neutral Emotion Sample Reviews

User Review	Prob.	Category
Very accurate with leaves/flowers, a little more hit-or-miss with bark. Ads are easy to X out of, and don't stop you from accessing the lists of options or additional info. You can also save a folder of your finds. I use it a lot.	0,979195	education
Heads up on points plus cash numbers. More combinations can be found only by selecting the first point plus cash offer displayed. Even if the points plus cash offer doesn't work for your particular situation, by going through the point plus cash offer displayed, even if the numbers don't work for you, if available, other points plus cash combos can be found in this area of the app.	0,978885	travellocal
The app is good, you just need to be patient to enable you get your match	0,977682	dating
This app is pretty decent at identifying items. If you want more accurate results, be sure to get in close on any branding, button layouts, or specific design elements. I have not tried it as a translator yet.	0,977446	tools
So far just used it for the first time and it pretty much gets what you're saying but leaves a few things out. Left to its own interpretations AI will do what it will.	0,976416	art-design

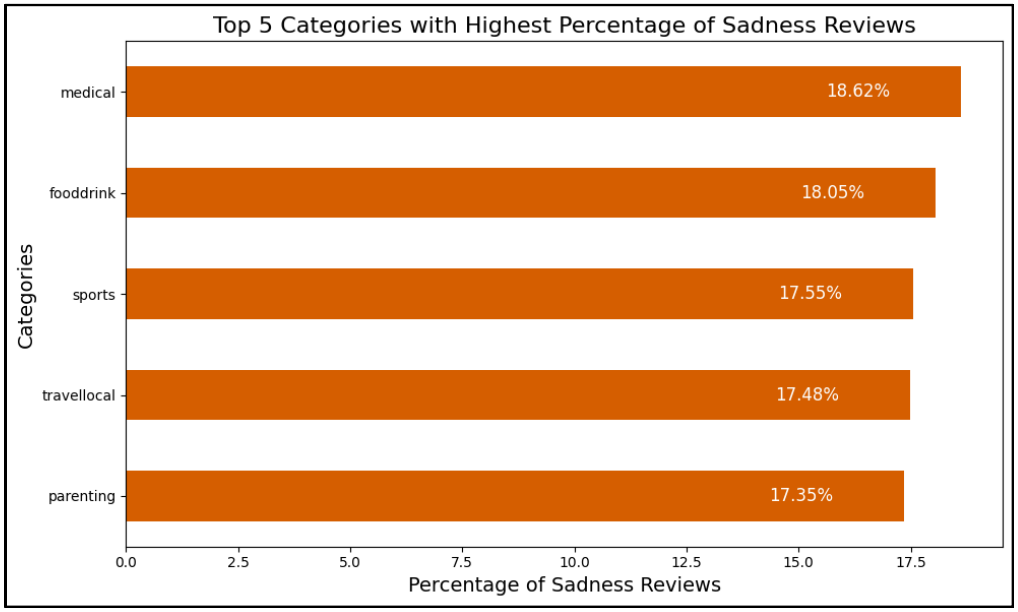

Figure 11. Sadness Emotion and Top Categories

The sixth category - sadness - is one the negative side emotions and it is dominant factor mostly on medical (18.62%), food & drink (18.05%), sports (17.55%), travel & local (17.48%) and parenting (17.35%) categories. As like the previous category (joy), it is crucial to understand the sadness category for marketing decision-making, since it reflects the other polarity. Table 8 presents the sample reviews for sadness category.

Table 8. Sadness Emotion Sample Reviews

User Review	Prob.	Category
always has been my go-to app when i'm feeling down. i feel like if no one can understand me, at least an AI-programmed bot can talk to me without having any hard feelings at all. i also rely on chatGPT to find information and other educational purposes. one of the best apps that has ever been made so far and a breakthrough in history.	0,992787	productivity
I love this game.coz it's too fast and I won 6 times after opening it. pls download it to make u happy and feel unlonely if u are lonly	0,989861	games
Been an emotional rollercoaster felt so lonely an so sad, been so upset with had let myself become in to tell others about love 😔	0,989718	healthfitness
When I am down and feeling sad the word of Our Lord God is the one that gets me through my day of hardship and sadness of seeing my Lords children suffering because of their little faith in their hearts. God bless America and God bless us all AMEN 🙏🙌😔	0,989651	booksreference
I am writing this app one star because all of my Emojis have disappeared I have constantly reached out to help & feedback about this issue and have yet to hear from anyone no customer service available I am not happy with this app and if I do not hear something back from customer service as soon as possible I will be uninstalling this app and letting everyone know how I feel about this app very unhappy.	0,989509	personalization

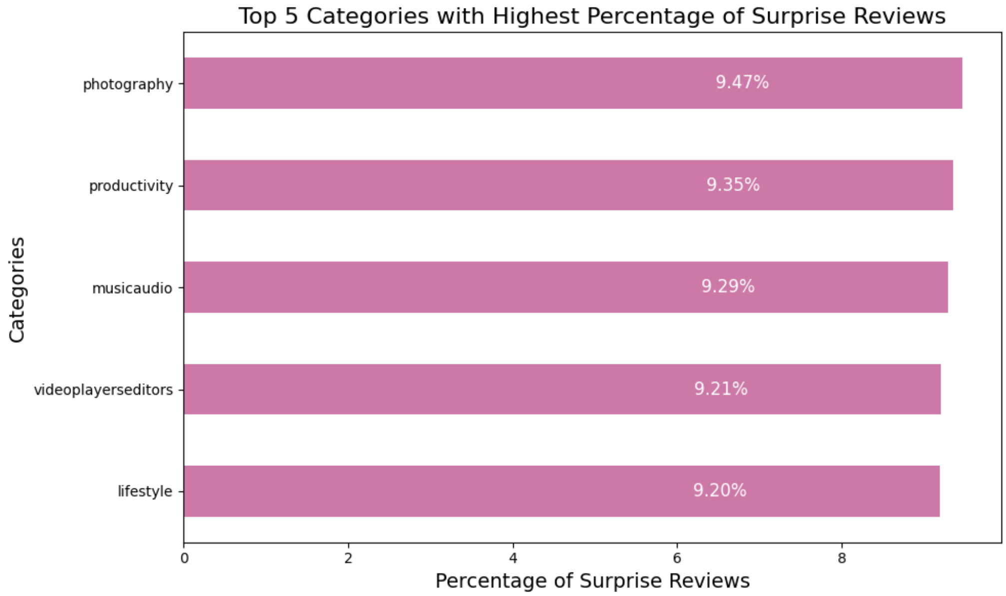

Figure 12. Surprise Emotion and Top Categories

The last category -surprise- is similar to anger category as it is not an usual dominant emotion category in the application categories. It is included in photography (9.47%), productivity (9.35%), music & audio (9.29%), video players & editors (9.21%) and lifestyle (9.20%) categories. Although it is not a popular dominant emotion in the reviews, it would help to understand what are the surprising elements for the users in market. Table 9 includes the sample reviews for the surprise emotion category.

Table 9. Surprise Emotion Sample Reviews

User Review	Prob.	Category
I really used to loved this app but i was disappointed because when i opened it i was shocked because there is only 2 stories that I can read offline, maybe it went like this when i tried to update it. Please do something about it, thankyou.	0,986199	booksreference
really love this app. was shocked there no cost. probably just sold my soul. would be alot better if it gave you the calories etc for the foods when you type them in.	0,985614	tools
I'm surprised by the wisdom and inspiration on this app. taste and see. you won't be disappointed	0,985509	booksreference
Honestly i was skeptical ay first since i never heard of this company.Price is cheap too.But i was amazed this camera easily competes with cameras priced way more.I have a 50$ camera and 3k security system.I bought this cheap camera to put in my trucking yard just for heck of it.So surprised by the build quality and as well as the cloud service.Definetly recommended.	0,985508	videoplayerseditors
i am amazed with the results. It can identify the stone name. yet it can not tell if it is fake or original. but actually, it's something that normal app can tell.	0,985427	lifestyle

Conclusion

The study focuses on the emotional spectrum in US market by 34 application categories and concludes the results in four sections. The first section includes the correlation between emotions in general and positive correlation between anger and disgust, negative correlation between joy and neutral, disgust and neutral, and sadness and joy are concluded. The first section highlights the neutrality in user reviews which can be the signal of utilitarian motives or mixture of emotions in expressions. It also shows the relationship between specific emotion sets which is the base point for further evaluation.

The second section focuses on spectrum and highlights the dominance of neutrality and adds the joy, sadness, disgust, anger and suprise as the secondary dominant emotions. The fear emotion category is found dominant rarely in the categories. Since the second sections shows the overall view of the emotion spectrum, it is the starting point for the further analysis such as examination of emotions by polarities and evaluation of emotions individually.

The third section uses the rating scores included in the reviews as a base point and classifies the reviews into negative, neutral and positive categories. Since the data is already decided by the owner of the reviews, it can be helpful as a starting point for the attitude of the users. However, inclusion of sentiments to the polarity of review contributes to better understanding of user reviews. Detection of which emotions are paired with negative polarity (neutral, sadness, disgust, anger), neutral polarity (neutral, sadness, disgust, surprise, joy) and positive polarity (neutral, joy, suprise, sadness) are indicators of users' emotions.

The final section details the individual emotions by the mobile application categories. The top 5 mobile applications categories are concluded for seven emotions, which leads to most valuable insights about the emotion categories. Anger emotion is related to finance and dating, disgust emotion is related to dating and social, fear emotion is related to auto & vehicles and travel & local, joy emotion is related to family and books & reference, neutral emotion is related to weather and video players & editors, sadness emotion is related to medical and food & drink, and finally surprise emotion is related to photography and productivity categories. This pairing between emotions and application categories shows the utitiarian and hedonic side of the mobile applications and user experiences.

Discussion

The study concludes the emotional spectrum of mobile application user reviews with four aspects including correlation of emotions, emotion distribution in categories, polarity and granularity of sentiments, and individual emotion exploration. The integrated approach employed in this study helps to evaluate mobile user experience in an comprehensive way and indicates the fundamental implications for the experience side. In addition to theoretical and comprehensive approach, the study employs the transformers-model based sentiment analysis which has advantage in terms of context and better than lexicon-based methodologies, so understanding of user expressions is relatively better by this combination.

The previous studies focus on the emotion side of user reviews in sub-contexts involving finance (Huebner et al., 2018), augmented reality (Pinarbasi & Canbolat, 2018), mental health (Alqahtani & Orji, 2020), education (Arambepola et al., 2024), and online travel agency (Hossain & Rahman, 2024). In the Turkish language scope of sentiment analysis, several contexts such as Covid 19 vaccines (Karakol & Cömert, 2023), social media posts about destinations (Çevrimkaya, 2023), multimedia learning material (Özgür et al., 2024) are included in the previous studies. This study focuses on the concept with a comprehensive approach and adds the novelty of an integrated approach to current literature.

Managerial side of this study refers to better understanding of the market with a detailed approach in consumer side through sentiment analysis. The rating scores (1 to 5) can already signal the positive and negativity side of the reviews, however, a detailed analysis regarding emotion spectrum would help to companies about the specific expressions and aspects of their customers. One of the other practical implication of the finding of study refers to usage of emotions knowledge for dual side in competitive environment. Detecting the company's own applications feedbacks in terms of emotion can show the satisfied / dissatisfied areas, however, evaluation of emotion diversity regarding the competitors' applications can help for competitive actions.

This study elucidates the emotion spectrum with various mobile application categories. The first limitation of the study refers to the descriptive approach of research design, since the study focuses on the categories and emotion spectrum in an overall level. In addition, sample-based extensions such as inclusion of additional markets, languages or focusing on specific categories can also be used in future research studies. The second limitation of the study is the approach level of emotions, as the study focus on the text content only and extract the emotions. Detailed approaches can elaborate the specific extensions of the emotion spectrum for the future research. Emotion spectrum topic can be studied with review persuasiveness, emotional contagion between users, impact on customer responses in the conceptual side. Finally, this study does not employ longitudinal approach, therefore, longitudinal studies can offer opportunities since the emotions and time-dimension relationship has the potential for scientific researches.

References

Alboqami, H., Al-Karaghouli, W., Baeshen, Y., Erkan, I., Evans, C., & Ghoneim, A. (2015). Electronic word of mouth in social media: the common characteristics of retweeted and favourited marketer-generated content posted on Twitter. *International Journal of Internet Marketing and Advertising*, *9*(4), 338-358.

Alqahtani, F., & Orji, R. (2020). Insights from user reviews to improve mental health apps. *Health informatics journal*, *26*(3), 2042-2066.

Arambepola, N., Munasinghe, L., & Warnajith, N. (2024, February). Factors Influencing Mobile App User Experience: An Analysis of Education App User Reviews. In *2024 4th International Conference on Advanced Research in Computing (ICARC)* (pp. 223-228). IEEE.

Bai, X. (2011). Predicting consumer sentiments from online text. *Decision Support Systems*, *50*(4), 732-742.

Bhadane, C., Dalal, H., & Doshi, H. (2015). Sentiment analysis: Measuring opinions. *Procedia Computer Science*, *45*, 808-814.

Bickart, B., & Schindler, R. M. (2001). Internet forums as influential sources of consumer information. *Journal of interactive marketing*, *15*(3), 31-40.

Çevrimkaya, M. (2023). Destinasyonlara Yönelik Sosyal Medya Paylaşımlarının Duygu Analizi. *Kent Akademisi*, *16*(3), 1907-1929. https://doi.org/10.35674/kent.1316264

Cheung, C. M., Lee, M. K., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities. *Internet research*, *18*(3), 229-247.

Ekman, P. (1992). An argument for basic emotions. *Cognition & emotion*, *6*(3-4), 169-200.

Felbermayr, A., & Nanopoulos, A. (2016). The role of emotions for the perceived usefulness in online customer reviews. *Journal of Interactive Marketing*, *36*(1), 60-76.

Guo, J., Wang, X., & Wu, Y. (2020). Positive emotion bias: Role of emotional content from online customer reviews in purchase decisions. *Journal of Retailing and Consumer Services*, *52*, 101891.

Hartmann, J. (2022). Emotion English DistilRoBERTa-base. Retrieved from https://huggingface.co/j-hartmann/emotion-english-distilroberta-base/

Herrando, C., Jiménez-Martínez, J., Martín-De Hoyos, M. J., & Constantinides, E. (2022). Emotional contagion triggered by online consumer reviews: Evidence from a neuroscience study. *Journal of Retailing and Consumer Services*, *67*, 102973.

Hossain, M. S., & Rahman, M. F. (2024). Detection of readers' emotional aspects and thumbs-up empathy reactions towards reviews of online travel agency apps. *Journal of Hospitality and Tourism Insights*, *7*(1), 142-171.

Huebner, J., Frey, R. M., Ammendola, C., Fleisch, E., & Ilic, A. (2018, November). What people like in mobile finance apps: An analysis of user reviews. In Proceedings of the 17th international conference on mobile and ubiquitous multimedia (pp. 293-304).

Hussain, S., Guangju, W., Jafar, R. M. S., Ilyas, Z., Mustafa, G., & Jianzhou, Y. (2018). Consumers' online information adoption behavior: Motives and antecedents of electronic word of mouth communications. *Computers in Human Behavior*, *80*, 22-32.

Jalilvand, M. R., Esfahani, S. S., & Samiei, N. (2011). Electronic word-of-mouth: Challenges and opportunities. *Procedia Computer Science*, *3*, 42-46.

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American society for information science and technology*, *60*(11), 2169-2188.

Karakol, D. U., & Cömert, Ç. (2023). COVID-19 Aşıları için Türkçe Tweetlerle Duygu Analizi. *Dicle Üniversitesi Mühendislik Fakültesi Mühendislik Dergisi*, *14*(4), 639-652. https://doi.org/10.24012/dumf.1358519

Khoa, B. T., & Huynh, T. T. (2022). How do customer anxiety levels impact relationship marketing in electronic commerce?. *Cogent Business & Management*, *9*(1), 2136928.

Kim, H. Y., Kim, Y. K., Jolly, L., & Fairhurst, A. (2010). The role of love in satisfied customers' relationships with retailers. *The International Review of Retail, Distribution and Consumer Research*, *20*(3), 285-296.

Kozinets, R. V., De Valck, K., Wojnicki, A. C., & Wilner, S. J. (2010). Networked narratives: Understanding word-of-mouth marketing in online communities. *Journal of marketing*, *74*(2), 71-89.

Langan, R., Besharat, A., & Varki, S. (2017). The effect of review valence and variance on product evaluations: An examination of intrinsic and extrinsic cues. *International Journal of Research in Marketing*, *34*(2), 414-429.

Lazarus, R. S. (1991). *Emotion and adaptation*. Oxford University Press.

Lee, S. (2018). Enhancing customers' continued mobile app use in the service industry. *Journal of Services Marketing*, *32*(6), 680-691.

Liang, T. P., Li, X., Yang, C. T., & Wang, M. (2015). What in consumer reviews affects the sales of mobile apps: A multifacet sentiment analysis approach. *International Journal of Electronic Commerce*, *20*(2), 236-260.

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism management*, *29*(3), 458-468.

Liu, J., Li, C., Ji, Y. G., North, M., & Yang, F. (2017). Like it or not: The Fortune 500's Facebook strategies to generate users' electronic word-of-mouth. *Computers in Human Behavior*, *73*, 605-613.

McColl-Kennedy, J. R., Patterson, P. G., Smith, A. K., & Brady, M. K. (2009). Customer rage episodes: emotions, expressions and behaviors. *Journal of Retailing*, *85*(2), 222-237.

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams engineering journal*, *5*(4), 1093-1113.

Mingyu, J. (2024). Google Play Scraper. GitHub repository. Retrieved from https://github.com/JoMingyu/google-play-scraper

Mondal, A. S., Zhu, Y., Bhagat, K. K., & Giacaman, N. (2024). Analysing user reviews of interactive educational apps: a sentiment analysis approach. *Interactive Learning Environments*, *32*(1), 355-372.

Mudambi, S. M., & Schuff, D. (2010). Research note: What makes a helpful online review? A study of customer reviews on Amazon. com. *MIS quarterly*, 185-200.

Naseem, U., Razzak, I., Khan, S. K., & Prasad, M. (2021). A comprehensive survey on word representation models: From classical to state-of-the-art word representation language models. *Transactions on Asian and Low-Resource Language Information Processing*, *20*(5), 1-35.

Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science*, *31*(3), 521-543.

Nyer, P. U. (2000). An investigation into whether complaining can cause increased consumer satisfaction. *Journal of consumer marketing*, *17*(1), 9-19.

Özgür, A., Sağlam, F., Burkay, G. E. N. Ç., & Altun, A. (2024). Çokluortam Öğrenme Materyalinde Duygu Salınımını Belirleme. Pamukkale Üniversitesi Eğitim Fakültesi Dergisi, 1-29. https://doi.org/10.9779/pauefd.1178733

Park, D. H., Lee, J., & Han, I. (2007). The effect of on-line consumer reviews on consumer purchasing intention: The moderating role of involvement. *International journal of electronic commerce*, *11*(4), 125-148.

Permana, M. E., Ramadhan, H., Budi, I., Santoso, A. B., & Putra, P. K. (2020, November). Sentiment analysis and topic detection of mobile banking application review. In *2020 Fifth International Conference on Informatics and Computing (ICIC)* (pp. 1-6). IEEE.

Pınarbaşı, F., & Canbolat, Z. N. (2018). Evaluation of augmented reality mobile applications in turkey market: A data mining approach to consumer reviews. *Changing Organizations: From the Psychological and Technological Perspectives içinde*, 187-197.

Plutchik, R. (2001). The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. *American scientist*, *89*(4), 344-350.

Purnawirawan, N., Eisend, M., De Pelsmacker, P., & Dens, N. (2015). A meta-analytic investigation of the role of valence in online reviews. *Journal of Interactive Marketing*, *31*(1), 17-27.

Sally, M. S. (2023). Why are consumers dissatisfied? A text mining approach on Sri Lankan mobile banking apps. *International Journal of Intelligent Computing and Cybernetics*, *16*(4), 727-744.

Sensor Tower. (2024). Top Charts. Retrieved from https://app.sensortower.com/top-charts?category=all&country=US&date=2024-05-06&device=iphone&os=android

Van Rossum, G., & Drake Jr, F. L. (1995). Python tutorial.

We Are Social., & Meltwater. (2024). Digital 2024. Retrieved from https://wearesocial.com/uk/blog/2024/01/digital-2024/

Westbrook, R. A. (1987). Product/consumption-based affective responses and postpurchase processes. *Journal of marketing research*, *24*(3), 258-270.

Yang, L., Li, Y., Wang, J., & Sherratt, R. S. (2020). Sentiment analysis for E-commerce product reviews in Chinese based on sentiment lexicon and deep learning. *IEEE access*, *8*, 23522-23530.

Zhang, C., & Laroche, M. (2020). Brand hate: a multidimensional construct. *Journal of Product & Brand Management*, *30*(3), 392-414.

GENİŞLETİLMİŞ ÖZET

Günümüz tüketicisinin yoğun biçimde kullandığı ve gündelik hayatlarında önemli bir yere sahip olan mobil uygulamalar günümüz mobil dünyasının önemli parçalarından biridir. Mobil uygulama çeşitleri ve kullanım amaçları her geçen gün zenginleşirken, finans, fitness, sağlık, seyahat gibi farklı ana kategorilerdeki mobil uygulamalar tüketicilerin günlük yaşamlarına eşlik etmektedir. Öte yandan, bu ana kategorilere ek olarak teknolojinin gelişmesi ve tüketici deneyimlerinin çeşitlenmesiyle birlikte yeni bağlamlar ortaya çıkmaktadır. Literatürde yer alan önceki çalışmalar, mobil uygulamaların satışı (Liang vd., 2015), sürekli kullanım (Lee, 2018) ve memnuniyetsizlik (Sally, 2023) gibi çeşitli kavramlara odaklanmaktadır. Çevrimiçi değerlendirme konusunun içerikle ilgili bağlamı literatürde halihazırda konu yönüne (Permana ve diğerleri, 2020) ve duygu yönüne (Mondal ve diğerleri, 2024) göre incelenmiştir. Ancak önceki çalışmaların bağlamları sınırlıdır ve mobil uygulama ekosistemini anlamak için içerik ve duyguya yönelik kapsamlı ve bütünleşik bir yaklaşım gerekmektedir. Bu çalışma, çeşitli mobil uygulama kategorilerini daha geniş bir veri seti üzerinde inceleyerek, ekosistemin geniş kapsamıyla ilgili olan araştırma boşluğuna odaklanmaktadır.

Araştırma amacına uyumlu olarak bir örneklem inşa etmek amacıyla bu çalışmada Google Play Store'daki verilere ulaşmak için Python programlama dili (Van Rossum ve Drake,1995) ve google-play-scraper (Mingyu, 2024) modülü kullanılmıştır. Örneklem kararı, Sensor Tower web sitesindeki (Sensor Tower, 2024) uygulama kategorilerine dayanmaktadır ve çalışmanın örneklemi, Google Play mağazasındaki tüm kategorileri kapsamaktadır. Örnekleme 06.05.2024 verilerine göre yapılmış olup, 34 kategoriden ilk 25 uygulama kaynak olarak seçilmiştir. Kategori adları Tablo 1'de sunulmaktadır. Çalışma ABD pazarına ve İngilizce yazılmış incelemelere odaklanmaktadır. Google Play Store'da filtrelenen kullanıcı yorumları için mobil uygulamalara ait "en alakalı" kullanıcı yorumları alınmıştır. Veri toplama 08.05.2024 tarihinde gerçekleştirilmiş olup, analizin ilk aşaması için 302.679 inceleme elde edilmiştir. Örneklemi ele almak üzere kullanılan yöntem olarak duygu analizi (sentiment analizi) tercih edilmiştir. Kullanıcı incelemelerinin içerik yönünü anlamaya yönelik yöntemlerden biri olan duygu analizi, tüketici araştırmalarında kullanılan faydalı metodolojilerden biridir. Duygu analizinde yer alan kutuplar (olumlu-olumsuz-nötr) düzeyinden daha ileri giderek belirli duyguları tespit etmeyi amaçlayan çalışmada, dönüştürücü model (transformers model) kullanılarak duygu analizi gerçekleştirişmiştir. Çalışmada "Emotion English DistilRoBERTa-base" (Hartmann, 2022) isimli transformers modeli kullanılmıştır. Araştırmanın bulguları dört ayrı bölümde sunulmuştur. Birinci bölümde genel olarak duygular arasındaki korelasyon yer almakta ve öfke ile tiksinti arasındaki pozitif korelasyon, neşe ile nötr, tiksinme ile nötr arasındaki negatif korelasyon, üzüntü ve sevinç arasındaki ilişki sonucuna varılmaktadır. İlk bölüm, faydacı amaçların veya ifadelerdeki duygu karışımının sinyali olabilecek kullanıcı incelemelerindeki tarafsızlığı vurgulamaktadır. İkinci bölüm ise spektruma odaklanarak tarafsızlığın hakimiyetini vurgulayıp ve ikincil baskın duygular olarak sevinç, üzüntü, tiksinti, öfke ve şaşkınlığı eklemektedir. Korku duygusu kategorisi kategorilerde nadiren baskın bulunmuştur. Üçüncü bölümde, incelemelerde yer alan derecelendirme puanları baz puan olarak kullanılmakta ve değerlendirmeler olumsuz, nötr ve olumlu olarak sınıflandırılmaktadır. Veriler zaten incelemelerin yazarları tarafından puan olarak (1,2,3,4,5) hali hazırda belirlendiğinden kullanıcıların tutumlarının anlaşılması için bir başlangıç noktası olarak faydalı olabilmektedir. Öte yandan, hali hazırda mevcut olan olumlu, olumsuz, nötr kutuplarındaki sınıflandırmanın üzerine çeşitli duygu kategorilerinin eklenmesi, kullanıcı yorumlarının daha iyi anlaşılmasına katkıda bulunmaktadır. Hangi duyguların negatif kutup (nötr, üzüntü, tiksinti, öfke), nötr kutup (nötr, üzüntü, tiksinti, sürpriz, sevinç) ve pozitif kutup (nötr, sevinç, şaşkınlık, üzüntü) ile eşleştiğinin tespiti, kullanıcıların belirli duygu ifadelerinin göstergesidir. Son bölümde ise bireysel duygular mobil uygulama kategorilerine göre detaylandırılmıştır. Duygu kategorileri hakkında içgörülere ulaştıracak şekilde yedi duygu türü için en fazla rastlanan beş mobil uygulama kategorisine yer verilmiş, böylece belirli duygular ile belirli uygulama kategorilerinin eşleşmesine ulaşılmıştır. Öfke duygusu finans ve flört uygulama kategorileriyle, tiksinme duygusu flört ve sosyal uygulama kategorileriyle, korku duygusu otomobil & araç kategorisi ve seyahat & yerel kategorisiyle, sevinç duygusu aile ve kitaplar & referans uyglama kategorileriyle, nötr duygu ise hava durumu ve video oynatıcılar & editörler kategorileriyle ilgilidir. Ayrıca, üzüntü duygusu tıp ve yeme-içme mobil kategorinde en sık rastlanmış olup, son olarak sürpriz duygusu fotoğrafçılık ve üretkenlik uygulama kategorilerinde sık olarak rastlanmıştır. Duygular ve uygulama kategorileri arasındaki bu eşleştirme, mobil uygulamaların ve kullanıcı deneyimlerinin faydacı ve hazcı yönünü dair izler taşımaktadır.

Çalışma, mobil uygulama kullanıcı incelemelerinin duygusal çeşitlilik dağılımını, duyguların korelasyonu, kategorilerdeki duygu dağılımı, duyguların kutupluluğu üzerinden ayrıntı duyguların tespiti ve tekli duyguların duygu keşfi dahil olmak üzere dört unsurla sonuçlandırmıştır. Bu çalışmada kullanılan bütünleşik yaklaşım, mobil kullanıcı deneyiminin kapsamlı bir şekilde değerlendirilmesine yardımcı olmakta ve deneyim yönüne yönelik temel çıkarımlara işaret etmektedir. Bu çalışmanın yönetimsel tarafı, tüketici tarafında duygu analizi yoluyla detaylı bir yaklaşımla piyasanın daha iyi anlaşılmasını ifade etmektedir. Mobil uygulama değerlendirmelerinde yer alan puanlar (1'den 5'e kadar) hali hazırda değerlendirmelerin olumlu ve olumsuz yönlerini işaret edebilir; ancak duygu çeşitliliği ve dağılımına ilişkin ayrıntılı bir analiz, şirketlere müşterilerinin belirli ifadeleri ve yönleri hakkında yardımcı olacaktır. Araştırma bulgusunun diğer uygulamaya yönelik çıkarımlarından biri de rekabet ortamında duygu bilgisinin rekabet açısından iki yönlü kullanılmasına ilişkindir. Firmanın kendi uygulamalarına ilişkin geri bildirimlerin duygu açısından tespit edilmesi memnun olunan/memnun olunmayan alanları gösterebilir, öte yandan rakiplerin uygulamalarına ilişkin duygu çeşitliliğinin değerlendirilmesi rekabetçi eylemlerin geliştirilmesine yardımcı olabilir. Bu çalışma duygu çeşitliliği ve dağılımını çeşitli mobil uygulama kategorileri ile bir arada aydınlatmaktadır. Bu yaklaşımı takip edecek olan daha ayrıntılı bakış açıları, gelecekteki araştırmalar için duygu spektrumunun belirli uzantılarını detaylandırabilir. Duygu spektrumu konusu, kavramsal açıdan ikna edicilik, kullanıcılar arasındaki duygusal etkilenmeler, müşteri tepkileri üzerindeki etkisi gibi konuları ile bir arada incelenebilir. Ayrıca gelecekteki araştırma çalışmalarında farklı ilave pazarların, farklı dillerin dahil edilmesi veya belirli kategorilere odaklanma gibi örnek bazlı uzantılar da kullanılabilir. Son olarak, duygu ve zaman-boyut ilişkisinin bilimsel araştırmalar için potansiyel taşıması nedeniyle boylamsal çalışmalar fırsatlar sunabilir.