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## Overview of Financial Applications for Investing on the Stock Exchange - Regression Models and Sentiment Analysis

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Submitted 19/11/21, 1st revision 03/12/21, 2nd revision 19/12/21, accepted 05/02/22

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### **Abstract:**

**Purpose:** The aim of the review is to analyze the available investment applications that can be downloaded by Google or Apple in terms of available functionality.

**Design/methodology/approach:** Correlation and regression analyses were carried out on the obtained data. Next, aspects of the application that most often appear in reviews were distinguished and sentiment analysis was carried out.

**Findings:** The results obtained indicate an extremely important share of the specified functionalities of the application in its global evaluation, and allow for the presentation of specified aspects both in terms of sentiment and evaluation of the application.

**Practical Implications:** The results of the study could be useful for developers and consumers of financial applications. For the first, the analyses carried out can point to directions of development that are particularly relevant. For the recipients, it is important to indicate the wide range of possibilities offered by the applications.

**Originality/Value:** The obtained results indicate the importance of analyzing individual application functionalities in order to understand the complexity of the problem of application evaluation in popular websites.

**Keywords:** Financial Applications, sentiment analysis, stock market, artificial intelligence, application quality, regression models.

**JEL classification:** D12, D47, D53.

**Paper type:** A research study.

**Funding:** Research was developed and funded in project POIR.01.01.01-00-0162/19 entitled "The WSE Data platform as an innovative system using artificial intelligence techniques to support investment decisions on the capital market" co-financed by the European Regional Development Fund under the Intelligent Development Operational Programme.

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## 1. Introduction

The market of financial applications for investing is a highly development area. The variety of solutions allows to choose both beginners and advanced investors in solutions, whose task is to support and implement investment activities. However, finding the right application is not easy (Sohangier *et al.*, 2018, Mariana, Rui Ferreira, and Nuno 2017). There are many difficulties that a potential person encounters when wanting to take advantage of this facility. One of the most common is the fact that there is no single, centralized application evaluation system, but only the ratings issued with the reviews by users. The user rating expressed in the number of asterisks or reviews is a reference, but it is also affected by many errors. One of the most common is the preference to give extreme ratings. A person using the application is more likely to give 1 or 5 stars in the rating than the middle options.

Additionally, for two reviewers, 5 or 4 stars do not have to mean the same thing, because the evaluation of the application is subjective and each reviewer sets his or her own benchmark. This results in a significant discrepancy between the ratings and the reviews. In many applications there are errors that are fixed in subsequent versions of the tool, there is no single possibility to add reviews to a particular version of the application. Reviews relating to errors of previous versions occur even though the product is released in subsequent releases. Analysis of reviews is particularly difficult if at some point there was a program defect that was reported by the application users (Huebner *et al.*, 2018; 2019). This makes it difficult to assess the application properly.

In addition, the app developers themselves can buy or promote favorable reviews, or leave negative on their competitors' app pages. The emotional feedback that may or may not influence the decision to buy or not to buy a product is also important (Karjaluo *et al.*, 2019; Amoroso and Chen 2017). The difficulties mentioned above are commonly encountered when choosing the desired tool. This analysis aims at reviewing the most popular applications for investing in two aspects. The first aspect refers to the design and implemented functionality of the application (Munoz-Leiva, Climent-Climent, and Liebana-Cabanillas 2017). The second aspect is to examine the relationship between the ratings and reviews with the presented functionalities, in terms of the number of asterisks, sentiment analysis of the reviews or references to the application functions in the review. The aim of the review is to try to outline the image of the application to invest and, based on the information obtained, to draw conclusions about possible improvements and development directions. In order to outline the area of research the following questions were asked:

1. Which investment applications are most popular? Does the popularity of the application depend on the number of downloads, evaluations, reviews or is it a resultant of these components?
2. What aspects/functions of the applications used for investing are the most popular and appear in the largest number of applications?

3. Is the occurrence of popular functions related to the evaluation of the application?
4. Are the evaluation of the application and the review related to each other?
5. Are the positive or negative phrases in the reviews related to the evaluation and which aspects are most frequently cited in the reviews?

Based on the analyzed literature, similar reviews have already been carried out for health, sports and financial applications. Based on the results obtained, it has been shown that the popularity of the application is related to the number of downloads and the evaluation obtained. The more positive the evaluation, the more the number of downloads increases (Chihong *et al.*, 2020; Yaron, 2020). Additionally, the authors of the articles pointed out that on the application market there are many tools with very similar functions, which also have similar ratings. It was pointed out that before installing and selecting an application, a potential user has certain assumptions and ideas about the appearance and functions of the application (Declan, McKillop, and Stewart 2020). The more it is fulfilled, the more positive the evaluation of the tool. In addition, a certain distinctness of ratings and reviews was pointed out. It results from the fact that positive ratings often do not contain or contain residual.

## 2. Research Methodology

Analyzed applications used for trading can be divided into internal categories, which are defined on the basis of functions to be performed by the application (Tongaonkar *et al.*, 2013; Samuel and Chong 2017; Hitkul *et al.*, 2018). One of the most popular categories are applications created by banks, used for investing within a given institution. The second category divides applications according to the type of investment that can be made for it. These can be investments on Polish or foreign exchanges, investments on bullion or bitcoins. The third category refers to the degree of advancement of investors who will use a given tool. There are applications for beginner investors, in which there are tutorials and instruction guides, and the opposite end are applications for people familiar with the ways of investing, whose task is to support the investment process and the presence of additional functions, whose task is to increase the profit of a potential investor.

### 2.1 Data

For the purpose of the analysis, it has been decided to choose the widest possible range of available investment applications from both the Google Play and App Store (Smailovic *et al.*, 2013; Dridi, Atzeni, Reforgiato, and Recupero, 2019). A minimum of 10,000 downloads and assigning to a general finance category was a prerequisite for the application to be analyzed. 115 applications were qualified for preliminary analysis. Then the selection was made and it was decided to leave 111 applications.

The following data were obtained for the analysis: Google Play and App Store ratings, Number of ratings, Number of downloads. Based on the analysis of articles and applications, 5 main features, most often implemented in applications, were distinguished. These are search for historical events, alerts/notifications, digital version of reports, data visualization and personalization. Each of these functions was assigned a scale: 0 - lack of a given function, 1 - basic version of the function, 2 - presence of the function, 3 - extended presence of the function. Reviews were downloaded using `google.play.reviews.scrapers 0.1.2` command in Python.

## 2.2 Application Functions

Within the application's specified functions, available solutions were analyzed in terms of searching for historical events (Goul, 2012; Mir Riyanul, 2014). The evaluation of the function took place after checking whether it is possible to select a given quotation and check its value backwards, for a given period of time, depending on the level of advancement of the function, a rating was granted. The second function included alerts and notifications.

In order to check the function, it was analyzed whether the application is sending notification requests and what kind of notifications are they. The possibility of personalizing notifications for given quotations or threshold values was also analyzed. The third function checked the possibility and advancement of visualization of available data. Financial data have extensive presentation capabilities, the evaluation of a given application took into account the type, number and detail of charts, as well as the ability to adjust the data and their visualization to user preferences. The last function included all those aspects that could be adjusted to the user in various degrees, so that the application could meet the preferences and needs of a given person.

## 2.3 FinMARS – Financial Mobile App Rating Scale

The Financial Mobile App Rating Scale (Huebner *et al.*, 2019) was also used to analyze the application. This scale consists of 6 sections, which in total contain 34 questions. The purpose of the assessment is to be able to compare one application to another in terms of functionality and to refer to a tool that allows a reliable assessment of a given financial application.

Section A concerned questions related to engagement, curiosity, interaction and number of alerts in a given application and consisted of 5 questions. Section B referred to the functioning of a given application, ease of navigation, gesture control and construction logic (4 questions). Section C dealt with the subject of graphic reception, color scheme and stylistic compatibility of the application, which consisted of 3 questions. Section D contains 10 questions related to the perception of the application before and during the initial stages of its use, it focuses on issues related to the accuracy of the description in the store, brand awareness, the frequency

of updates, the presence of the tutorial, access requests displayed or price list transparency. Section E deals with the value of the application in terms of compatibility of the various platforms on which it is present, clarity and transparency of notifications or the possibility of exporting data and consists of 6 questions. The last section refers to financial and economic behavior and in the 6 questions is intended to examine whether the application can lead to increased financial knowledge, understanding of economic mechanisms or general awareness.

## **2.4 Sentiment Analysis**

Based on the reviewed solutions, it was decided to choose VADER - Sentiment Analysis as the preferred solution to analyze application reviews. VADER stands for Valence Aware Dictionary for Sentiment Reasoning. Sentiment Analysis allows to measure emotional language characteristics using linguistic methods, NLP and text analysis. Reactions are analyzed and evaluated in a dictionary with an appropriate weight. Sentiment analysis can be performed in two approaches. The first approach assumes using only statistical methods for text analysis. It ignores the order of words or the context of the statement. The second approach integrates statistical and linguistic methods in order to better understand the analyzed statement.

The obtained data can be divided into two categories, the first one assigns a neutral, positive or negative label. The second one adds a scale to the above categories, so the word can be more or less positive/negative. Using VADER allows to measure sensitivity to Polarity and Intensity of emotional labels. Polarity is an attribution of whether the sentiment is neutral, positive or negative. Intensity measures how positive or how negative is sentiment in analyzed text. This approach allows to obtain Valence score which is scale from -4 to +4. Most negative sentiment is -4, neutral is around zero, and most positive is +4. To calculate this score VADER refers to implemented dictionary that consist of words and other lexical features, such as emoticons (:D, :P), acronym connected with sentiment (TLDR, LOL) slang words.

Additionally, in this tool are implemented selected heuristics, that improve sentiment scoring. Occurrence of these heuristic induces tracking relations between terms in case of word-order. One of the heuristics is punctuation, which means, that sentence with punctuation signs are treated as more intensive than without it. Another heuristic is capitalization, text in capital letters is treat as more intensive than normal letter. Third heuristic is degree modifiers, which recognize booster words, and treat sentence with them as more or less intense, specifically to meaning of intensifiers. Four heuristic is taking into account conjunctions, which may lead to shifting in polarity in mixed sentence. Last important heuristic is changing polarity because of occurrence of negation. Algorithm analyze sequence of 3 words, that allows to detect over 90% of existing negation, that change polarity sign. VADER packages can be imported as a new module in Python, but also are included in NLTK package, consisting of several techniques of natural language processing.

### 3. Results

A number of analyses were carried out in order to obtain answers to the research questions raised. Based on the survey, 137 evaluations of various investment applications were obtained. Table 1 presents the results of correlation between the examined variables and basic descriptive statistics such as averages and standard deviations.

**Table 1.** Descriptive statistics and intercorrelates for study variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Star rating (1)		0.27*	0.37 ***	0.65 ***	0.32 **	0.55 ***	0.51 ***	0.50 ***	0.45 ***
Number of star ratings (2)			0.58 ***	0.08	0.17	-0.09	0.08	0.21	0.02
Functions (3)				0.19	0.28 **	0.05	-0.01	0.07	-0.02
Engagement (4)					0.26 *	0.52 ***	0.36 ***	0.42 ***	0.34 **
Functionality (5)						0.13	0.46 ***	0.20	0.47 ***
Aesthetics (6)							0.38 ***	0.31 **	0.26 *
Trust Signaling (7)								0.22 *	0.67 ***
App Value (8)									0.41 ***
Financial Behavior (9)									
Mean	4.15	2.30	1.40	3.04	3.07	3.09	2.86	3.09	2.93
SD	0.5	0.6	0.7	0.8	1.4	0.7	0.6	0.6	0.6

**Note:** Correlation n=137. \*p<0.05. \*\*p<0.01. \*\*\*p<0.001.

**Source:** Own study.

Based on the conducted correlation analysis, a relationship was shown between the evaluation of the application and all the variables studied, which determines the relevance of the research question two. The highest correlation coefficient was obtained between the evaluation of the application and engagement, aesthetics, trust signaling and app value.

However, correlations of the other variables were also significant and ranged from 0.27 to 0.65. An analysis of the significance of the differences between the two correlation indicators was also carried out. There is no statistically significant difference between the star rating correlation with engagement, aesthetics, trust signaling or app value. There is a statistically significant difference between engagement and financial behavior (p<0.01) and correlation rates lower than this aspect (functionality, functions, number of star rate). The differences were checked

between the correlations of individual aspects with the old rating. Based on the obtained results two polynomial regression models were built for the rating variable. The results obtained for the models are presented in Table 2.

**Table 2.** Polynomial regression for tested models

Model	R <sup>2</sup>	SS	df
1 (without Vader Score)	0,73	26,27	16,00
2 (with Vader Score)	0,75	27,07	18,00
	MS	SS	df
1 (without Vader Score)	1,64	8,35	120
2 (with Vader Score)	1,50	7,55	118,00
	MS	F	p
1 (without Vader Score)	0,07	23,58	0,00
2 (with Vader Score)	0,06	23,52	0,00

**Note:** MS=mean squared errors; SS=sum of squares; R<sup>2</sup>=proportion of the variance; F=statistic whether independent variables are significant; df=degree of freedom; p=statistical significance.

**Source:** Own study.

In order to perform analyses to answer research question 4 two multimodal regression models were built, one taking into account the VaderScore review and the other not taking into account the review in the model. The difference between the models was 2% of the explained variance and is not statistically significant. Based on the conducted regression analysis it was shown that popularity and better evaluation of the application are the resultant of many components. Both the number of downloads, quality of re- views, number of functions, as well as implemented functionalities measured with Fin- MARS tool. The result of the explained variance for the second model was 75%, which is a highly satisfactory result and allows to predict the evaluation of a given investment application based on its features and functionalities.

The next step of the calculations was to analyze the sentiments of the reviews. 261 127 sentences from the reviews were analyzed, which gave a total of 62 182 reviews. One application had about 400-600 reviews, and the average score from the application was 2.95. The same or a similar number of reviews were attempted for each assessment. This resulted in an imbalance in the number of sentences between the assessments (negative assessments usually consist of more sentences than neutral or positive assessments). The number of ratings for 1 star: 12456, 2 stars: 12433, 3 stars: 12419, 4 stars 12460, 5 stars: 12414.

Based on the aspects of financial applications distinguished in the article by Huebner *et al.* (2018), it was decided to include them in the analysis of investment applications, as a subset of applications from the financial area. The highlighted aspects of the application are the presence of advertisements, user interface, price list, memory/battery usage, compatibility, connection, privacy settings,

login/registration, guide, sounds, videos, notifications, text quality, location services, upgrades and stability. The above-mentioned aspects of the application were detected in the existing collection of user reviews. Based on the available data, a logistic regression was carried out, the results of which are presented in Table 3.

**Table 3.** *Logistic regression for application aspects*

Logistic Regression	
Accuracy	0,70
Macro F1	0,56
Micro F1	0,70

*Source:* Own study.

A two-stage sentiment analysis was carried out. The first stage contains information about the number of negative, neutral and positive sentences assigned to a particular star rate (from 1 to 5). Table 4 presents the division of sentences depending on the analysis of the application, as shown in Figure 1.

**Table 4.** *Number of sentences assigned to particular star rate*

Star rating:	1	2	3	4	5
All	120645	61415	42791	24217	12059
Negative	64818 (54%)	35419 (58%)	22106 (52%)	5077 (21%)	3511 (29%)
Neutral	46078 (38%)	22874 (37%)	13234 (31%)	8782 (36%)	3145 (26%)
Positive	9749 (8%)	3122 (5%)	7451 (17%)	10358 (43%)	5403 (45%)

*Source:* Own study.

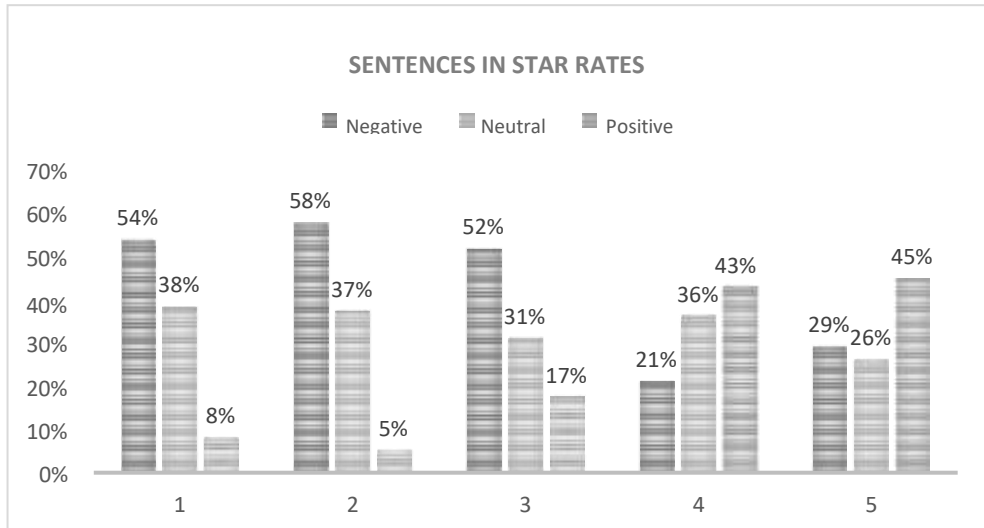
Based on the analysis, it can be seen that for the lowest marks, i.e., 1, 2 and 3, there is a predominance of negative sentences, only the highest marks, i.e., 4 and 5, has the advantage of positive sentences. It should be noted that each assessment consisted of a different, sometimes significantly different number of sentences.

Most sentences were attributed to extremely negative opinions (about 120 thousand) and negative opinions (about 61 thousand). Then the number fell to 12 thousand sentences for the highest rated opinions. The percentage designation refers to the share of a specific group of sentences within the ratings.

The second stage analyzed the occurrence of negative, neutral and positive sentences in the highlighted aspects of the application. The obtained results are presented in Table 5 and Figure 2. There is possible that one sentence was assigned to more than one aspect of application.



**Figure 1.** Number of sentences divided by assigned star rate



*Source:* Own elaboration based on research.

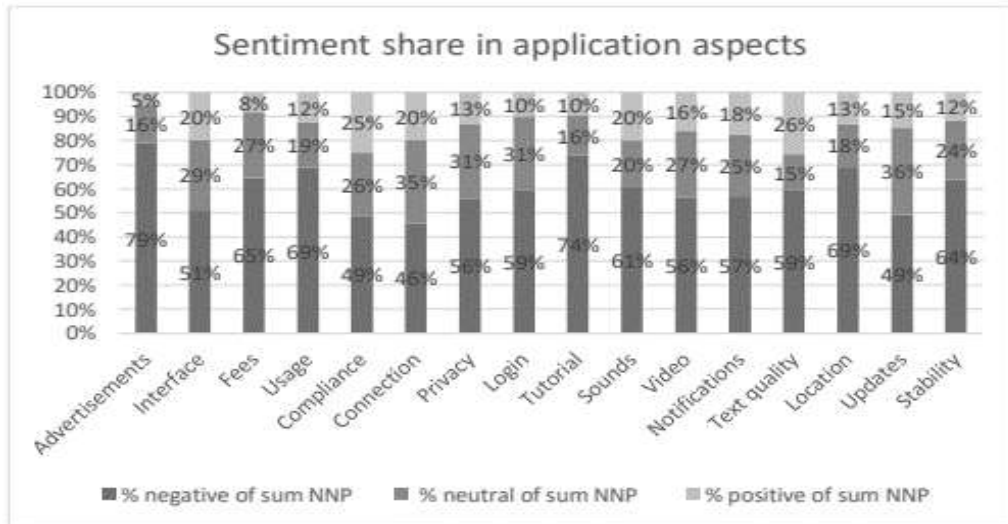
**Table 5.** Number of sentences assigned to particular application aspects

	Negative	% of sum	Neutral	% of sum	Positive	% of sum	SUM
Advertisements	7693	79%	1557	16%	505	5%	9755
Interface	8720	51%	4989	29%	3362	20%	17071
Fees	10728	65%	4523	27%	1373	8%	16624
Usage	11996	69%	3272	19%	2163	12%	17431
Compliance	7782	49%	4196	26%	4001	25%	15979
Connection	5958	46%	4523	35%	2549	20%	13030
Privacy	8675	56%	4789	31%	2019	13%	15483
Login	8172	59%	4273	31%	1356	10%	13801
Tutorial	5732	74%	1274	16%	757	10%	7763
Sounds	6865	61%	2213	20%	2255	20%	11333
Video	1392	56%	675	27%	397	16%	2464
Notifications	12899	57%	5736	25%	3992	18%	22627
Text quality	3688	59%	942	15%	1604	26%	6234
Location	7809	69%	1985	18%	1497	13%	11291
Updates	5953	49%	4337	36%	1784	15%	12074
Stability	11078	64%	4242	24%	2011	12%	17331
Sum	125140		53526		31625		210291

*Source:* Own study.

Based on the analysis, most of the negative sentences were assigned to the functionality, stability, notifications, usage and fees.

**Figure 2.** Percentages of sentences assigned to particular application aspects



**Source:** Own elaboration based on research.

The most negative sentences concerned advertisements (79%) and tutorials (74%), in no aspect did the share of negative sentences fall below 46%. The most positive sentences were related to the compliance aspect (25%), and the least advertisements (5%). The data obtained also allows for the analysis of the percentage of individual aspects within a given sentiment (Table 6).

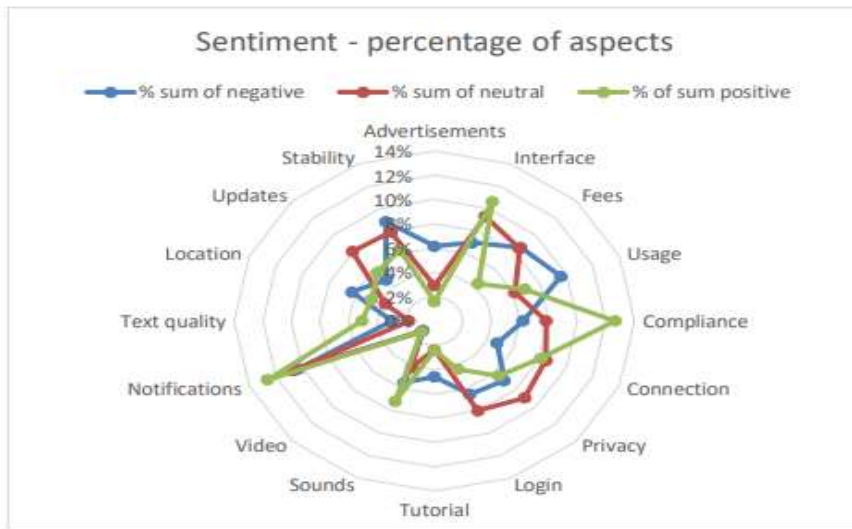
**Table 6.** Number of aspects assigned to particular sentiment

	Negative	% of sum	Neutral	% of sum	Positive	% of sum
Advertisements	7693	6%	1557	3%	505	2%
Interface	8720	7%	4989	9%	3362	11%
Fees	10728	9%	4523	8%	1373	4%
Usage	11996	10%	3272	6%	2163	7%
Compliance	7782	6%	4196	8%	4001	13%
Connection	5958	5%	4523	8%	2549	8%
Privacy	8675	7%	4789	9%	2019	6%
Login	8172	7%	4273	8%	1356	4%
Tutorial	5732	5%	1274	2%	757	2%
Sounds	6865	5%	2213	4%	2255	7%
Video	1392	1%	675	1%	397	1%
Notifications	12899	10%	5736	11%	3992	13%
Text quality	3688	3%	942	2%	1604	5%
Location	7809	6%	1985	4%	1497	5%
Updates	5953	5%	4337	8%	1784	6%
Sum	125140		53526		31625	

**Source:** Own study.

Based on the data obtained, the notifications aspect represented 10% of negative sentences, 11% of neutral sentences and 13% of positive sentences. For positive sentences, the same result was achieved by the compliance aspect and below, the interface aspect (11%). The lowest share, regardless of the sentiment, was in the video aspect (1% each), similarly low shares were in the text quality (for negative and neutral sentiment), advertisements (for neutral and positive sentiment) and tutorial (for positive sentiment) (Figure 3).

**Figure 3.** Percentage of aspects assigned to particular sentiments



*Source:* Own elaboration based on research.

#### 4. Conclusion and Limitations of the Study

Based on the research carried out, it can be seen that the evaluation of a given application is closely related to the functions that this tool offers the user. Statistically significant correlations between aspects and functionalities of the application and the evaluation of the application on the portal were shown. Based on the obtained data, a polynomial regression was carried out, which allowed to explain 75% of the variance taking into account the sentiment analysis rate in the reviews of application assessments, and 73% not taking this rate into account.

This result indicates that the examined variables constitute the majority of factors influencing the assessment of a given application. Then a two-stage procedure was carried out for the highlighted aspects of the application. The first stage assumed the distinction based on available literature sources and popular compilations of application functionality. The second approach was aimed at checking the matching of the awarded categories with the existing set of reviews, which amounted to 0.70 Accuracy for the logistic regression model. The sentimental analysis allowed us to observe a number of information related to the general structure of the review, as

well as to its individual aspects. Despite a balanced set of reviews per application assessment, the number of sentences was significantly different. The highest number of sentences was in negative reviews, then the share of sentences decreased towards positive reviews.

The selected aspects were characterized by a higher percentage of negative sentences than the others, and these were advertisements and tutorials. In addition, an analysis was carried out, which allowed us to examine how individual aspects are distributed within a given sentiment. This allows us to observe which aspects, regardless of the sentiment, have a similar percentage, which are different, and to indicate which aspects have the highest or lowest percentage. The obtained results indicate the importance of analyzing individual application functionalities in order to understand the complexity of the problem of application evaluation in popular websites (Gurshobit, Singh, and Sharma 2018; Caetano 2018).

However, no significant share of the reviews themselves has been shown, only the number of stars awarded. The study was conducted on a set of applications used for investment; it indicates the limited application possibilities of the above study. It is recommended to relate the above results only to applications of the same or similar purpose, i.e., investment, and to cautious reference to applications from the financial industry (Santos and Rabello Lopes, 2019). The necessity of conducting similar research in other areas of the application is indicated in order to understand the existing mechanisms (Probierz, Gałuszka, and Dzida, 2021), and to deepen the level of exploration financial data (Gałuszka *et al.*, 2020a; 2020b).

**Acknowledgments:** *The work of Eryka Probierz was supported in part by the European Union through the European Social Fund as a scholarship Grant POWR.03.02.00-00-I029, and in part by the Silesian University of Technology (SUT) through a grant the subsidy for maintaining and developing the research potential in 2022 for young researchers in data collection and analysis. The work of Adam Gałuszka and Tomasz Grzejszczak was supported by the SUT Grant the subsidy for maintaining and developing the research potential, in 2022.*

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