User Preferences and Segments in App Store Marketing: A Conjoint-based Approach

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***Abstract*—Today, little is known about how the various elements involved in the presentation of mobile applications (apps) in app stores influence the download or purchase decision of potential users. Current publications primarily focus on the possibilities and technical tools of app store marketing based on best practices or experience. However, research on customer preferences with regards to the presentation of apps in app stores as well as the impact of single app store elements on purchase or usage decisions has yet to be addressed. In this context, the key research objectives of this paper are to not only analyze the impact of individual app store elements on customer choice but also see if the customers can be segmented into homogenous groups according to their preferences. Accordingly, this study will identify the relative importance of individual app store elements, from both a general or mass market perspective as well as a user segmentation perspective, and derive recommendations on how to successfully present mobile applications in app stores. With this objective in mind, a conjoint analysis of a fictitious mobile messaging app in the Apple App Store was carried out for the purpose of identifying the relative importance of app store elements in the mass market. It was followed by a Latent Class Analysis, which looked at how those preferences differed among different market segments.**

Keywords-Mobile App Marketing; App Store Elements; App Marketing; Consumer Preference; Conjoint Analysis; Market Segmentation; Latent Class Analysis.

I. INTRODUCTION

As discussed in [1], the number of mobile applications is steadily growing. More than a million applications are now available for Android and iOS in the respective app stores (i.e., GooglePlay and Apple App Store). Accordingly, the competition among individual app providers is constantly rising [2]. It has long since ceased to be enough to simply turn a good idea into an app. More and more, the question has become, which factors trigger the user's purchase decision. Numerous managers in the mobile phone business are now forced to deal with this situation and to define mobile app marketing strategies on how to achieve and defend a competitive position for their apps in the market.

Marketing plans and strategies are usually created according to the concept of the marketing mix, which also plays a key role in mobile app marketing [3]. The marketing mix should be an optimal combination of marketing tools from the areas of Product (product policy), Price (pricing policy), Promotion (communication policy) and Place (distribution policy) [4]. These "4Ps" are also the components of the app store marketing toolkit. Product policy starts at a very early stage and deals with the app idea and with the subsequent design of the application [3].

With regards to pricing policy both before and after the launch of the mobile app, a wide range of decisions have to be made. These decisions range from adequate price level to dynamic pricing strategies designed to systematically alter prices over time in order to react to changes in actual demand and current market conditions. However, pricing policy is limited by the possibilities and restrictions of the app stores. For example, the app stores may specify certain price points to be selected or not permit providers to offer trial versions for a limited period of time [5].

Distribution policy generally deals with all the marketing decisions and activities concerned with the delivery channel from the producer to the customer and therefore from production to consumption [4]. As early on as the development stage of an app, the distribution channel is determined, or at least influenced, by the technical implementation. So-called web applications, for example, can simply be made available for download per link or published via any webserver. The distribution channel for so-called hybrid und native applications, on the other hand, is the app store. Before use, they must be completely downloaded and installed on the mobile device. While native applications are created using the platform-specific development environment and programming language, web technology is usually used with hybrid applications. Additional development frameworks and tools, however, allow for further processing and compilation of this source code in a way that enables its distribution via an app store in a similar way to a native application.

Within the communication policy, we have to differentiate between activities inside and outside the app store. This includes advertising and other activities, which provide and disseminate information aimed at familiarizing the potential customer with the app and its features. App stores are usually the only official channel for users to buy and install new apps on their mobile devices. Thus, the communication policy within the app stores and the corresponding design of the various app store elements are of particular importance [6]. Here, it must be noted that each store has its own specific regulations and guidelines on how to publish an app for distribution as well as which elements can be used to present the app in the store.

However, although the regulations vary in detail, the core concepts and the core elements for the app presentation are quite similar.

All the aforementioned app marketing activities need to be aligned with the intended target group of the app. Hamka et al. argue that the mobile market is evolving at an ever increasing rate as is the behavior of mobile users. Accordingly, they suggest that it is an imperative to segment the market "i.e. divide the addressable market into segments that have a consistent demographic, psychographic or usage pattern" [7]. However, the options for segment specific app marketing are limited. Currently, when a mobile app is launched the app elements can be adapted to local markets by selecting national stores and providing market specific app elements (e.g., app descriptions in different languages). In addition, the app can be placed in categories that represent the general usage concept of the app. These categories range from educational to games to tools. That being said, while these groupings help the potential user search of a specific type of application, they do little to actively market to specific groups of potential users. This might be sufficient for standard applications targeting relatively homogenous user preferences found in mass markets. In contrast, user groups with a differing preference structure looking for non-standard apps would argue for a more segment specific approach in app store marketing.

In this context, the objective of this study is to first develop appropriate recommendations for the setup and design of important app store elements, to empirically validate common app store marketing best practices and to determine potential user groupings based upon preferences. For this reason, a conjoint approach was chosen to analyze user preferences and characterize the relative importance of different app store elements. Then, using the data collected as part of the choice based conjoint analysis, a latent class analysis was conducted. This analysis was used to discover user groups with similar preference structures according to the presentation of app store elements.

With this in mind, Section II presents a short discussion on related work and current best practices in app store marketing. Section III describes important elements of the presentation for mobile applications in app stores. The explanations refer to the example of the Apple App Store; can, however, to a great extent be generalized to include other app stores. In Section IV, the methodological approach of this study is then described. Significant results of the conjoint analysis and the subsequent latent class analysis are presented in Section V, before we finally discuss the central findings and recommendations for practical implementation in the concluding section.

II. RELATED WORK

Mobile app marketing is still a relatively new marketing topic. It was not until the first app stores emerged that the necessity for a market-oriented way of thinking when developing and marketing mobile apps started to become apparent [5]. In principle, we can say that many well established concepts from general marketing practices are transferable to mobile app marketing. Consequently mobile app store marketing adopts standard marketing principles and tools and adapts them to the needs of the app specific market.

Current literature on mobile app marketing predominantly focuses on guidelines and recommendations for the successful monetization of app concepts. For example, the topic of app marketing can be found as part of the technical literature on app development in which the monetization of the app in the app store is seen as being the final step in the app development process [5][8][9]. Additionally, more specialized publications focusing on mobile app marketing are available as well [2][6][10][11]. However, most of these publications comprise structured guidelines and extended checklists on how to successfully monetize mobile applications based on the authors' experience or the discussion of successful case studies. In contrast, scientific research on app stores and app (store) marketing is rather rare today. Only few publications have so far dealt with individual aspects of app stores, mainly focusing on app ranking mechanisms and fraud [12][13][14], pricing strategies [15] or recommendations and user reviews [16][17].

Against this background, a significant research gap can be observed with regard to the availability of empirically based recommendations on the market-oriented configuration of app store elements. The suggested research approach, a study measuring customer preferences and segments based on a conjoint analysis, has been applied to software selection processes and even to mobile application development [18][19], but is rather new to the specific area of app store marketing. Accordingly, this study will attempt to answer the following two research questions:

- What are the most important app store elements from a user perspective and how should those elements be presented (based on the example of a messenger app)?
- Do users of mobile messenger apps (in Germany) fall into specific segments based on their preference structures for the presentation of app store elements?

Understanding the answer to these questions can help developers and marketers to more effectively reach the intended end user and communicate the product benefits.

III. APP STORE ELEMENTS

As stated above, the design of the various app store elements is one of the key instruments of mobile app marketing. Potential users search for suitable mobile applications in the app store and obtain information about their features and properties [3]. In order to acquire a common frame of reference for this study, we focused solely on the Apple App Store. There are various app stores for different mobile operating systems, which are characterized by different appearances, but which are fundamentally similar in terms of the possibilities to present mobile applications.

A fictitious messenger app was chosen to concentrate on the importance of the app store elements and prevent participants from being biased by earlier purchase decisions, knowledge of real-world app presentations or brand preferences. The Apple App Store can be accessed via several mobile devices. It is possible, for example, to open the app store via smartphones (iPhone) and tablets (iPad) to download applications. However, the number of elements is the same for all devices and always identical in each case.

In total, based on an analysis of the Apple App Store and best practices derived from the mobile app marketing literature in Section II, eight key app store elements were examined for this study, which will be described in more detail below. Moreover, the study also deals with variations of each of the attributes, which were compared and examined with regard to their influence on customer preference in terms of a purchase or usage decision. The fictitious messenger app was presented to the participants of the study based on the attributes and its selected attribute levels only. There was no prototype or trial-version in an app store available in this study.

A. *App Icon*

The app icon is seen as being one of the most crucial elements, as it is generally the first visual element that a potential user sees. The purely aesthetic design of the app icon can already have an effect on the development of user preference, for example in the way that the icon makes an impression and is taken as an indication of the quality of the app. The app icon and the app name are central design elements in many app stores, not least because they would be the first items that appear on the search results page [5][20]. In Figure 1, three icon versions are shown that were developed for a fictitious messenger app in the study.

(1) Modern/Specific „High quality“ version	(2) Balanced „Medium quality“ version	(3) Abstract „Low quality“ version

Figure 1. App Icons Variations

In the form of these icons, the intention is to refer to a particular messaging app, which is characterized by an especially high level of security. Best practice guidelines have been used to develop the design variations [21]. For example, the coloring and the legibility were varied in order to portray the spectrum from a representative "high" to a "low" quality design. The same is also true for the clarity of the graphic elements to visualize the messaging and security features of the app. While icon (1) has easy to understand graphical representations of messaging, icon (3) uses a vague illustration and faint writing. The consideration of the icon design as an attribute will allow an empirical verification of the aforementioned existing best practices in the study.

B. *App Name*

As mentioned above, the name of the app is also a central element with respect to the presentation of mobile applications in app stores, as it is shown in the app store's search and ranking lists and may therefore influence the user's purchase decision [5]. The app name should fulfil certain criteria in order to be easy to remember on the one hand, and easy to find via the app store's search algorithms on the other. Ideally, solutions to internationalize the name should also be available [3]. For the test app in the conjoint analysis, the same name was used for all three, but a claim was added for extra clarification. The claim varied from a simple allusion to security to a technical description, which is difficult for the average user to understand (high to low comprehensibility):

- „high“: SafeTalk – Your Safe Messenger
- „medium“: SafeTalk Secure Messenger
- „low“: Safetalk with AES-256 Encryption

C. *Reviews („stars“) and the number of reviews*

The reviews in the app store are assigned according to the star principle (1–5 stars) and are – together with the number of total reviews – an initial indicator for the user of how satisfied other users were with the app after downloading. A high number of stars is perceived as being a positive purchase recommendation [6]. App providers should note that star reviews are not immediately displayed for new apps but are only published once a meaningful average value can be calculated. In the Apple App Store, this means a minimum of 5 reviews. Apple also differentiates according to countries. At present, it is not possible for the user who is giving the review to interact directly with the app provider [3]. The following analysis includes the review alternatives none, three and five stars.

D. *Price*

Pricing is another element that is immediately displayed on the search result page and in all the app store's lists (for example in the „top charts“) and can therefore influence the user's purchase decision during the app selection process. For the analysis in this study, a cost-free version and three price points were chosen, which represented a low, a medium and a high price segment, respectively, in comparison to actual mobile messaging applications (0.89 EUR, 1.79 EUR, 2.69 EUR).

E. *Screenshots*

Screenshots are usually only visible in the detail view of an app, with the exception of the result page of the search feature. Here, the first of a total of five possible screenshots is already shown in the preview. Screenshots have several tasks: On the one hand, they should display the features of the mobile application and, on the other, communicate the app's design [3]. Screenshots offer crucial support to the descriptive text as many users do not read this or only read it in part and therefore rely heavily on the screenshots for their purchase decision [20]. App store users draw conclusions from the screenshots as to the aesthetics and user friendliness of the mobile application as a whole [6]. In this study, three different qualities of screenshots were created (high, medium, low), which vary with regard to recognisability and clarity of the functional elements of the mobile messaging app. The functional "low quality" screenshot, for example, displays purely functional content, whereas the notated "high quality" one highlights important core functions with accompanying explanations.

F. App Description

The descriptive text is the only element presented here, which appears solely in the detail view of an app once it is opened. The Apple App Store allows a descriptive text with a maximal number of 4000 characters [6]. The descriptive text is important for two reasons: Firstly, potential customers are presented with a list of sales arguments and secondly, the search algorithms of most app stores use the text to carry out corresponding search requests. As the optimization for search purposes was not the main focus here, the quality of the descriptive text was varied mostly in terms of comprehensibility. Here again, three levels of quality were created (high, medium, low). Whereas the user oriented "high quality" description used simple language and comprehensible wording, the complex "low quality" descriptive text was characterized by technical terms, which the average user would find difficult to understand. In addition, the text was automatically translated as is often the case in app stores, which reduced the comprehensibility yet further.

G. Server Location (as an additional attribute)

As a messenger with special focus on secure communication had been chosen as a fictional product for analysis, an additional attribute entitled "server location" was included in the study for evaluation. This is not an element of an app store in a narrow sense, but an important company related attribute of the app provider that can be emphasized within the app description. While the aforementioned attribute is used to measure how the quality of language influences user preferences, the server location is an example of how various app characteristics, even if just mentioned in the description, could have an impact on customer choice. Due to current discussions about data security in Germany [22], heightened customer awareness was assumed to be a significant influencer on customer preference. The goal of including this attribute was to test whether and to what extent such attributes contribute to the user's purchase decision in comparison to the other marketing-related app store elements. Server locations in the US, in Germany and an unknown server location were included in the study.

IV. METHODOLOGY

In identifying the most appropriate methodology to analyze the app store elements and provide potential user segmentation, multiple methods were considered. Conjoint analysis was identified as the most appropriate method to analyze the user preferences for the various app store elements. Based upon that decision, Latent Class analysis was selected to analyze the potential segmentation of users based on their preference structures. In the following, these methods and the reasoning for applying them in this study are discussed in detail.

A. Conjoint Analysis

The conjoint analysis is considered to be the standard method when investigating customer preferences and buying decisions. Traditional Conjoint Analysis (TCA) goes back to the year 1964 and was developed by the psychologist Luce and the statistician Tukey [23]. TCA, as well as all the subsequent versions of conjoint analysis, basically deals with the measurement of preferences for product attributes. Instead of asking the participants directly about the importance of attributes, conjoint analysis is based on the evaluation of product profiles. Each product profile consists of several attributes describing the product characteristics (e.g., brand, price, design, etc.). Different product profiles are derived by variation of attribute levels (e.g., high, medium, and low price). An analysis is always carried out in such a way that each product profile or "stimulus" has to be examined and assessed from a holistic perspective or *con*sidered *joint*ly) [24][25]. Instead of asking directly about the importance of a product attribute, conjoint analysis considers products as bundles of attributes, on which the customer decides and makes trade-off decisions. The approach is better aligned to real-world purchasing decisions and the part-worth utilities of the attributes can be decomposed by using statistical methods like regression analysis.

For this reason, the conjoint method is well suited to analyze the impact of different app store elements on the customer choice decision. As a result, the relevance of the key app store elements, derived from the practical literature, can be empirically validated based on the example of fictitious messenger app. The analysis also provides the relative importance of the different app store elements for market success. From a more practical perspective the results could be used by an app provider to determine the optimal app store configuration for the analyzed secure messenger app or to conduct market simulations based on different configurations. However, the study at hand focusses on the relative importance of the app store elements. The reference to a fictitious messenger app was required only because the conjoint analysis cannot be conducted based on a non-specific and generic "mobile app".

Since the mid-sixties, conjoint analysis research has evolved and produced several variants that can be divided into traditional and more recent approaches. Traditional Conjoint Analysis (TCA) can be applied by using trade-off or full-profile approaches but its significance in research has been declining since its first appearance due to limitations on the number of attributes as well as other methodological and statistical problems [26]. Of the more recent approaches, Choice Based Conjoint Analysis (CBC) and its variant, the computer-aided Adaptive Choice-Based Conjoint Analysis (ACBC) are taken into consideration for this study.

CBC is the most popular conjoint analysis today. In CBC, unlike TCA, discrete selection decisions are analyzed instead of preference decisions [27]. During CBC, the subject is therefore not asked to make an order of precedence of all the product profiles, but must select the preferred product profile within a set of alternatives or, if such an option is included, reject the choice by deciding on a "none option" [24][25] as shown in Figure 2. The ACBC is a computer-aided enhancement of classic CBC and includes an adaptive approach. This means that every piece of information supplied by the test subject during the course of the interview gradually reveals the formation of his/her preference structure so that the questions posed to him/her can be successively adapted to the answers

[28]. In this context, the first consideration for the study was to determine, which kind of conjoint analysis should be applied. For best results, CBC is recommended if the product bundle in question has around six attributes or less, however, the method can be carried out with up to ten attributes. ACBC has proved to be especially suitable if 5 to 15 attributes are to be examined. However, it is characterized by a more complex and time-consuming questioning process [29].

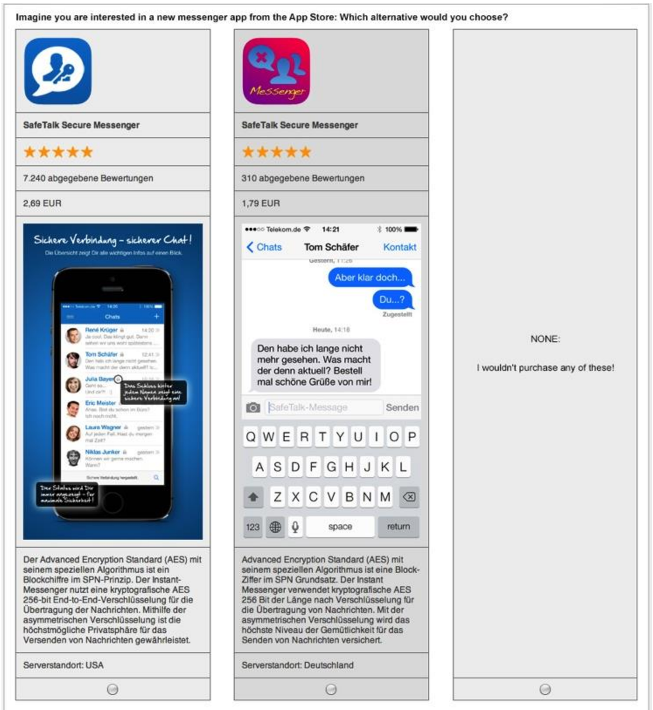

Figure 2. Example of a Choice Set in the Study

The number of attributes in this study was eight. Therefore, we had to determine the feasibility of using a CBC despite the large number of attributes, or if the larger effort of drawing up an ACBC would be needed. The form of the attributes provided an important aspect in making this decision. The amount of information that a test subject has to absorb and process in connection with every single attribute is especially important when calculating the reasonable maximum number of attributes. If the attributes being examined are graphic elements (e.g., app icon) or information, which can be quickly understood (e.g., price), then CBC could be a feasible option to carry out this type of analysis with more than six attributes [29].

Due to these criteria and considering the impact of an ACBC on the interview duration, CBC appeared to be the more suitable choice for the planned empirical survey. As far as survey design was concerned, it was important to define the form of the stimuli, specifically the question of which combination of attribute variations would constitute the stimuli and how the stimuli should be presented to each test subject. Here, the Full Profile Method was used, in which each product profile consists of all the attributes. As the number of attributes was already very high, we decided to present only two stimuli at a time so as not to overstrain the test subjects with regard to the information they had to evaluate. In order to create a selection situation as close as possible to a real-life purchase situation, a "none option" was also included.

Figure 2 shows a complete selection situation as an example of how it also appeared in the final survey. In addition to the (randomly) created selection sets, so-called hold-out sets were integrated into the survey. These special selection sets serve to analyze the validity of the prognosis. They are not integrated into the benefit evaluation and are used to evaluate the quality of the prognosis of the preference rating. Two of these sets were defined and included.

The conjoint analysis was carried out using the *Sawtooth* SSI Web 7 software package [30]. The main objective of the study was to measure the importance of the presented app store elements for mobile application purchase decisions. The study was conducted as an online survey. The website for the online survey was generated by the SSI Web 7 software, based on the aforementioned study design. The configuration of the CBC analysis and selected configuration parameters are summarized in Table I.

TABLE I. CONFIGURATION OF THE CBC ANALYSIS

Parameter	**Value**
Number of Random Choice Tasks	12
Number of Fixed Choice Tasks	2
Number of Concepts per Choice Task	2 (and an additional "none option")
Response Type	Discrete Choice (single select radio button)
Advanced Design Module Settings	Traditional Full-Profile CBC Design
Randomize Attribute Position within Concepts	No Randomize of Attribute Order

B. *Latent Class Analysis*

The idea behind consumer market segmentation is to divide the market into smaller homogenous groups for the purpose of product placement and targeted marketing [31]. By doing so, it becomes possible to better adjust the product and marketing efforts to consumer preferences or user requirements. According to [32], two approaches to market segmentation are a priori, aka common sense, or post hoc (i.e., data driven). A priori segmentation would define segments based on obvious group characteristics such as age, gender, geographical region and other general demographic information (e.g., men over 50 years living in a specific area). As a priori segmentation needs no analysis, it is much easier to select homogenous groups. While this approach might already be more effective than mass marketing, it relies on the discriminating power of directly observable group characteristics and ignores underlying variations of product needs and preferences of the individual user or consumer. Accordingly, post hoc segmentation tries to look at the results of studies specifically designed to understand the potential user's needs and preferences.

Conjoint based preference data can be used for segmentation based on latent class analysis (LCA) [33][34]. Having gained popularity in the 1990's, the model "detects segments of respondents having similar preferences based on their choices in CBC questionnaires" [35]. Latent class analysis takes CBC one step further in that it identifies groups of respondents that share specific preferences and estimates the average part-worth utility for each of the groups of respondents. In other words, the approach can be used to "discover segments of respondents who tend to have similar preferences manifest within the CBC (choice-based conjoint) data" [36].

In an LCA, the segmentation process is initiated by randomly selecting estimates of each group's part-worth utility values and then estimating the probability that a given respondent belongs to a specific group. Summing the logs of those probabilities, for all respondents across all questions results in the log-likelihood. In an iterative approach those probabilities are used to recalculate the logit weights until a "convergence limit" is reached [37]. Solutions can be calculated for a different numbers of groups. To determine the best number of groups, the log-likelihood cannot be used as it typically moves closer to zero as the number of segments increases. Thus, goodness-of-fit or Information Criterions (ICs) are used to determine the number of segments.

Two of the most common ICs are Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC) [38]. Often these ICs are automatically calculated by statistical packages, e.g., the Sawtooth software used in this study, with the expectation that they will provide some guidance with regards to selecting the appropriate number of segments. That being said, from a managerial perspective "the most important aspects to consider when choosing a solution for segmentation purposes are its interpretability and stability (reproducibility)" [36]. Once the group size has been determined, the data can be interpreted using the segment specific attribute importance as well as part-worth utilities rescaled for comparability.

V. Study Findings

Based on our methodical considerations an empirical study was conducted. The study was based on the presentation of the app store elements as discussed in the previous section in an online questionnaire. The survey was online between December 19, 2013 and January 10, 2014. Participants were acquired by using social media and various other online and offline channels of the RheinMain University of Applied Science in Wiesbaden, Germany. A total of 221 people participated in the conjoint analysis interview. Of these, 163 completed the interview in its entirety and are, therefore, included in the subsequent evaluation. Selected demographic characteristics of the study participants are shown in Table II below. The demographics show that the study might be biased by the participating media and design students and due to the resulting high proportion of iOS users compared to the lower usage rate in the total population in Germany of around 32 percent at the end of 2013 [39] and the underrepresentation of older user segments.

TABLE II. Demographics of the Study Participants

Characteristics	Absolute Number	Percentage
Mobile OS		
Apple iOS	78	47.9%
Android	78	47.9%
Blackberry OS	1	0.6%
Windows Phone/Mobile	5	3.1%
Symbian	1	0.6%
Purchased Apps		
None	32	19.6%
1–5	40	24.5%
6–10	20	12.3%
11–20	19	11.7%
21+	52	31.9%
Gender		
Female	70	42.9%
Male	93	57.1%
Ages		
18–24	66	40.5%
25–34	70	42.9%
35–44	21	12.9%
45–54	5	3.1%
55+	1	0.6%

The evaluation of the collected data took place in two steps: In the first phase, a counting analysis was conducted. This analysis can be used to calculate an outline of so called main effects. A main effect of an attribute level is calculated here as a proportion and reveals how many times a specific attribute level was chosen, divided by the number of times this attribute level was available for choice in the testing. Counting analysis is a simple way to get a first indication of the relevance of the attribute levels. As a second step, the part-worth utilities of the attribute levels were estimated based on a logit analysis to find the maximum likelihood solution for the data. Based on the results of the part-worth utility estimation, the relative importance of the individual app store elements were finally determined.

A. Counting Analysis

A counting analysis and the proportions that are calculated at this stage can be used to identify the "winner" of the different attribute levels. Table III shows the results of the counting analysis for all attributes and attribute levels considered in this study. The higher the proportion of an attribute level is, the stronger this attribute level may have influenced the choice of participants. For the app store element "Reviews (stars)" a five-star rating was the "winner" – which is not surprising. However, in comparison, choices with this attribute level were selected more than twice as often (0.421/0.158) as choices with no stars in the reviews.

TABLE III. SUMMARY OF STUDY RESULTS

Attributes and Attribute Levels	**Counts (Proportions of "Wins")**	**Part-Worth Utilities**
App Icon		
High quality	0.312	0.22215
Medium quality	0.262	-0.01639
Low quality	0.234	-0.20575
App Name		
SafeTalk – Your safe messenger	0.277	0.02744
SafeTalk Secure Messenger	0.247	-0.10392
Safetalk with AES-256 Encryption	0.283	0.07648
Reviews (stars)		
5 stars	0.421	0.73209
3 stars	0.229	-0.13465
No stars	0.158	-0.59744
Number of Reviews		
7.240 reviews	0.329	0.31666
310 reviews	0.320	0.26487
5 reviews	0.229	-0.19484
No reviews yet	0.198	-0.38669
Price		
Free of charge	0.385	0.60605
0.89 EUR	0.274	0.02966
1.79 EUR	0.238	-0.14028
2.69 EUR	0.180	-0.49543
Screenshots		
High quality	0.262	-0.02198
Medium quality	0.274	0.01437
Low quality	0.271	0.00760
App Description		
High quality	0.283	0.07434
Medium quality	0.269	0.01472
Low quality	0.256	-0.08906
Server Location		
Germany	0.373	0.52316
USA	0.224	-0.20529
Unknown	0.212	-0.31788

However, as mentioned before, this analysis can give a first indication of the relevance but does not provide measurements for the part-worth utilities of attribute levels and relative importance of the different attributes, i.e., app store elements.

B. Estimation of Part-worth Utilities

Part-worth utilities were calculated by using the multinomial logit estimation provided by the *Sawtooth* software for the CBC analysis. For the model estimation, a Chi Square of 473.7 was reported. Considering 18 degrees of freedom (26 attribute levels and 8 attributes) the Chi Square is much larger than the required 34.8 for a 0.01 level, which would mean that the choices of the respondents are significantly affected by the attribute composition [27]. The estimated part-worth utilities represent the relative desirability of an attribute level. The higher the value of a part-worth, the greater the impact of the corresponding attribute level on the buying decision. Part-values are automatically standardized, so that the result per attribute amounts to „0“. Reciprocally, this means that negative values can also arise. Table III shows the estimated values for all attribute levels. These should be interpreted to mean that a higher number corresponds to a higher part-worth utility and that this attribute variation therefore had a higher preference among the test subjects. If we look again at the attribute "Reviews (stars)“, it becomes evident that the attribute level „5 stars“ has a very high part-worth value with a positive value of 0.73209. The other two variations „3 stars“(-0.13465) and „no stars“(-0.59744) were less important for the purchase decision of the test subjects due to smaller values of the corresponding part-worth utilities.

C. Calculation of the Attribute Importance

The defined objective of the empirical study was not only to find out the utilities of the attribute variations but also to analyze each individual app store element in terms of its relative importance for an app purchase decision. Therefore, we must find a unit of measurement to express the relative importance of each attribute. The calculation is carried out by dividing the range of the part-worth of each attribute by the sum of the part-worth ranges of all the attributes. Hereby, the range is defined as the difference between the highest and the lowest part-value within the levels of an attribute [40]. The results can be seen in Table IV.

TABLE IV. RELATIVE IMPORTANCE OF ATTRIBUTES

Attribute	**Attribute Importance**
Reviews (Stars)	27.8%
Price	23.2%
Server Location	17.6%
Number of Reviews	14.9%
App Icon	9.0%
App Name	3.6%
App Description	3.3%
Screenshots	0.6%
Total	**100.0%**

The values reveal that the reviews according to the star principle have the largest influence on the purchase decision. Almost 28% of the decisions are based on this criterion. The highest part-worth utility and/or the most positive influence was of course an app review with 5 stars. The distance to the other attribute variations (3 stars, no stars) was the highest with this app store element compared to the other elements. This highlights the extremely high relevance of good reviews and the importance of this attribute for the perceived total utility of the corresponding app presented in the app store. As was to be expected, pricing has a high level of importance for the purchase decision, too. The test subjects reacted in a very price-sensitive way. It should also be noted that many apps are now offered at the Apple App Store for free or at a greatly reduced price at the beginning or at some stage of their life cycle for a certain period of time. A certain „freebie“ mentality is also reflected in the order of precedence in this study and shows that price is one of the most important criteria for an app. The app provider's server location differs from the other elements in as far as it is not a standardized app store element but the app developer‘s company-related element. Therefore, we can conclude that users not only include the app store's design elements into their purchase decisions, but also consider and evaluate outstanding and specific properties of the app. In this case, there was a particularly positive effect on the purchase decision if the messenger provider was located in Germany. The number of reviews relates to the reviews according to the star principle. Here, we see the tendency that the part-worth utility is perceived as higher, the more reviews an app has. An interesting aspect here is that the part-worth of the extreme scenario considered in the survey with 7,240 reviews did not substantially differ from the next level with 310 reviews. The distance to the next two steps (5 reviews, no reviews) is considerably larger, however. This means that an optimal number of reviews – which can be attained with a reasonable amount of effort on the part of the app provider – can be assumed to be more than 5, but not significantly higher than 310 reviews. The app icon is considerably less important than expected. Besides the screenshots and the star reviews, it is the third graphic element and easy for the potential buyer to understand. Nevertheless, the test subjects apparently did not assess the quality of the app on the basis of the icon but stuck to the very much more rational criterion of the reviews when making their purchase decision. The app name is of very low significance. Many users see it as a "frill" within the overall impression of the app store and it is therefore of little interest. The study results even show that the name "Safetalk with AES-256 Encryption," which was previously defined as the worst variation, actually had the highest partial benefit value. However, this could be a result of the specific setup and the sensitivity of the app users towards data security in Germany. The complicated name – even if not understood by the customers – may be associated with a highly sophisticated technological solution to protect the user from the danger of interception. The app's descriptive text is also of little importance in terms of decision making. This suggests that potential buyers do not take the time to read it or may be very familiar with the type of apps that have been tested here. It should be noted at this point that the descriptive texts used in the survey were relatively short. In real life, an app is mostly described in much more detail and using many more characters – the attention span could, therefore, be even shorter than for the texts used in the survey.

With a relative importance of 0.6 percent, the screenshots had the lowest influence on the purchase decision. Here, too, it was striking that the part-worth of the medium quality screenshots was the highest, followed by those of the worst quality. The highest quality level had the lowest part-worth value for the test subjects. Here we should note, however, that the differences recorded were marginal and the general result, i.e., that screenshots hardly influence purchase decisions, is predominant. This may also be due to the fact that the subject of the study, messaging app functions, is relatively well-known and simple and that therefore screenshots have only minor informational value as far as the app is concerned.

D. *Group Segmentation*

In order to better understand if these preferences are universal or if the user preferences fall into different groupings according to common preferences, a LCA was conducted as discussed in Section IV. Solutions were computed with the Sawtooth software package for a minimum of two and a maximum of seven groups considering typical ranges used in LCA studies [41][42]. As shown in Table V, the log-likelihood moves closer to zero as more segments are included in the solution. To determine the number of groups, the ICs mentioned in the methodology needed to be analyzed. The most common used ICs in LCA studies are Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) as mentioned before. Both criteria are based on the likelihood function but incorporate penalties to control for over fitting (to derive a parsimonious solution). The goal is to minimize the value of the IC where the lowest value indicates the best fitting model.

TABLE V. INVORMATION CRITERIA OF THE LCA

Group	Log-likelihood	AIC	BIC
2	-1637	3351	3569
3	-1562	3243	3572
4	-1497	3152	3593
5	-1437	3071	3624
6	-1409	3056	3720
7	-1373	3023	3799

However, as shown in the Table V, the two IC produce contrary results by supporting the two (BIC) or the seven (AIC) group solution. Such ambiguous results are not unusual in LCA and so [38] suggest that the choice of an IC has to consider the goal of the study. In this context, the BIC-preferred size can be interpreted as the minimum size for a parsimonious model and the AIC-pref erred size as a maximum when the exploration of population heterogeneity is in focus. The choice then has to be made "based on other kinds of fit criteria, on theory, or on subjective inspection of results" [38]. As the aim of the study at hand was to explore the population heterogeneity, a subjective inspection of the two-group solution offered only limited insights into potential market segments. On the other hand, the seven-group solution was selected for further interpretation and provided clear groupings with distinct preferences.

As discussed before in the methodology section, the relative importance of the attributes and the preferred attribute levels can be used to interpret the preference structures of the computed user segments. In a first step, the group specific relative importance of the attributes was inspected. Considering an equal relative importance of each of the eight attributes for the group members, a relative importance of 12.5 percent could be expected. Accordingly, those attributes with a relative importance greater than 12.5 percent could be interpreted as truly impacting the purchase decision. In Tables VI through XII, those attributes with a relative importance greater than

12.5 percent were highlighted in grey. Once the attributes of importance were identified, the preferred attribute level was determined based on the group specific estimation of the re-scaled part-worth utilities. At the attribute level, the (rescaled) part-worth utilities for each of the three versions of the app element were compared. Accordingly, the version with the highest part-worth utility represented the preferred configuration of that app store element. The information about the group specific importance of the attributes and the preferred group levels where then used to define an appropriate characterization of preference structure for the presentation for app store elements.

The first group shown in Table VI was focused on quality as indicated by the high preference for 5 stare ratings. They were also very interested in the server location being in Germany. Price was not as important and the group members would prefer to pay a moderate price (1.79 EUR) for an app with the appropriate quality features. From this perspective the mindset of this group can be characterized as "Quality for Money". More than 13 percent of the sample (N=23) have been assigned to this segment.

TABLE VI. LCA MARKET SEGMENTATION: GROUP 1

Groups and Attributes	Relative Importance	Preferred Attribute Level (Part-worth Utilities)
Group 1 ("Quality for Money", N=23)		
Server Location	**44%**	**Germany**
Reviews (stars)	**16%**	**5 stars**
App Description	12%	High quality (User-oriented)
App Icon	11%	Medium quality (Balanced)
App Name	6%	Safetalk w. AES-256 Encryption
Number of Reviews	6%	7.240 reviews
Screenshots	3%	High quality (Notated)
Price	2%	1.79 EUR

Similar to the "Quality for Money" group, the preferences in the next group, presented in Table VII, were heavily influenced by quality as indicated by the importance of 5 star ratings, the server location in Germany, and the preferred high number of user reviews.

TABLE VII. LCA MARKET SEGMENTATION: GROUP 2

Groups and Attributes	Relative Importance	Preferred Attribute Level (Part-worth Utilities)
Group 2 ("Free Rider", N=30)		
Reviews (stars)	**23%**	**5 stars**
Server Location	**20%**	**Germany**
Price	**19%**	**Free of charge**
Number of Reviews	**18%**	**7.240 reviews**
App Description	7%	Medium quality (Tech Savvy)
App Name	5%	SafeTalk – Your safe messenger
App Icon	5%	High quality (Modern/Specific)
Screenshots	5%	Med. quality (Design-focused)

The main differentiating factor being that they did not want to pay for it. Given that they expect high quality for free, this segment was characterized as the "Free Rider" segment. More than 18 percent (N=30) of the respondents are classified in this group.

Just the opposite can be seen in group three. As seen in Table VIII, this group is actually willing to pay "top dollar" for high quality apps. Accordingly, this group has been described as the "Premium" group.

TABLE VIII. LCA MARKET SEGMENTATION: GROUP 3

Groups and Attributes	Relative Importance	Preferred Attribute Level (Part-worth Utilities)
Group 3 ("Premium", N=14)		
Reviews (stars)	**22%**	**5 stars**
Price	**20%**	**2.69 EUR**
App Icon	**14%**	**High quality (Modern/Specific)**
Server Location	11%	Germany
App Name	11%	Safetalk w. AES-256 Encryption
App Description	10%	Medium quality (Tech Savvy)
Number of Reviews	9%	310 reviews
Screenshots	3%	Med. quality (Design-focused)

In this case, quality is seen as 5 star ratings and usage of the modern/specific design icon. This segment is on the smaller side, accounting for only 9 percent (N=15) of the respondents, but their willingness to pay a high price for an application make them a relevant segment.

Similar in size is the "free at all costs" group seen in Table IX. This group has been deemed so as price is the only attribute that matters to them.

TABLE IX. LCA MARKET SEGMENTATION: GROUP 4

Groups and Attributes	Relative Importance	Preferred Attribute Level (Part-worth Utilities)
Group 4 ("Free at all Costs", N=15)		
Price	**67%**	**Free of charge**
Reviews (stars)	8%	5 stars
Screenshots	7%	Low quality (Functional)
App Name	5%	Safetalk w. AES-256 Encryption
Number of Reviews	4%	310 reviews
Server Location	3%	USA
App Description	3%	Medium quality (Tech Savvy)
App Icon	3%	Medium quality (Balanced)

This group also accounts for about 9 percent (N=15) of the respondents but unlike the premium group, if the app is not free, this group will most likely not consider it. Similarly, the largest segment, accounting for 33 percent (N=54) of respondents, also prefers apps that are free of charge, however, that is less important than high ratings and reviews. This group has been labeled the "Socially Motivated Majority" group.

TABLE X. LCA MARKET SEGMENTATION: GROUP 5

Groups and Attributes	Relative Importance	Preferred Attribute Level (Part-worth Utilities)
Group 5 ("Socially Motivated Majority", N=54)		
Reviews (stars)	**30%**	**5 stars**
Number of Reviews	**25%**	**7.240 reviews**
Price	**20%**	**Free of charge**
App Icon	8%	High quality (Modern/Specific)
Server Location	7%	Germany
App Description	6%	High quality (User-oriented)
App Name	4%	SafeTalk – Your safe messenger
Screenshots	1%	Low quality (Functional)

As seen in Table X, the members of this group are heavily influenced by the experiences and ratings of other users and thus might be inclined to follow "word-of-mouth". Confirming what was assumed during the design of the app elements, group 6 is a perfect example of the German customer's heightened awareness about data security, accounts for 13% of the respondents this group is very concerned with security and has thus received the title "privacy concerned"

TABLE XI. LCA MARKET SEGMENTATION: GROUP 6

Groups and Attributes	Relative Importance	Preferred Attribute Level (Part-worth Utilities)
Group 6 ("Privacy Concerned", N=22)		
Server Location	**52%**	**Germany**
App Icon	12%	High quality (Modern/Specific)
Number of Reviews	10%	310 reviews
Reviews (stars)	9%	5 stars
App Description	8%	Low quality (Complex)
Price	6%	Free of charge
App Name	2%	SafeTalk Secure Messenger
Screenshots	2%	Low quality (Functional)

As seen in Table XI, server location is of utmost importance, so much so that it is the only attribute influencing their purchase decision. Most likely due to the recent NSA disclosures [22], they have a strong preference for a server location in Germany. However, their willingness to pay for this is questionable. Table XII shows the outlier group. Accounting for only 3% of the respondents, this group is not only small, their preferences did not conform to any expectations.

TABLE XII. LCA MARKET SEGMENTATION: GROUP 7

Groups and Attributes	Relative Importance	Preferred Attribute Level (Part-worth Utilities)
Group 7 (Outliers/Not Considered, N=5)		
Price	**34%**	**Free of charge**
Number of Reviews	**20%**	**No reviews yet**
Reviews (stars)	12%	5 stars
App Name	8%	SafeTalk – Your safe messenger
Screenshots	7%	Low quality (Functional)
App Description	7%	Low quality (Complex)
App Icon	6%	Medium quality (Balanced)
Server Location	6%	Unknown

Accordingly, this group has not been analyzed to any further extent. However, the existence of such a group indicates that the decision to use a maximum of 7 groups the LCA was a good estimate.

VI. IMPLICATIONS

This study confirms the observation from best practices, that reviews have a major influence on the user's purchase decision. Not only from a mass market perspective, but also among the majority of the market segments. Average ratings according to the star principle as well as the number of reviews given determine the buying decision of an app to a very large degree. These two criteria, however, cannot be directly influenced by the app provider – reviews are made by the app user and are published by the app store with no prior screening. Nevertheless, there are numerous possibilities for the provider to influence the reviews, at least to some extent. Active review management should therefore be conducted. Review reminders within the app can for example help to continuously increase the number of reviews. It is advisable to wait for a certain period of time before displaying review reminders as the probability of receiving a positive review is higher when the app has been used for a period of time. Reviews can also be stimulated by actively reacting to user feedback, i.e., by responding to reported software bugs or considering suggestions for improvements in upcoming updates.

The possibilities for the provider to influence the price are often strongly determined by the costs. In addition, the price decision can depend on the app's life cycle or even some important seasonal factors (special offers on public holidays for example). Thus, a low price level may not be an option and the findings of the conjoint analysis cannot be transferred to a general recommendation on an adequate pricing strategy. However, if it makes sense for the type of app in question, a free version can be offered, which can be supplemented by additional content per in-app-purchase. This "freemium model" takes the user's initial price-sensitivity into account. Revenue generation is then postponed to a later phase of usage. Alternatively, the results of the Latent Class analysis suggest that there are certain groups willing to pay a premium for quality applications. Accordingly, while mass marketing may be less effective for higher priced apps, effectively targeting the appropriate market segment can be another solution in such situations.

Another important finding is that particular attention should be drawn to app-specific properties if these could positively influence sales. From a mass market perspective, this applied to the server location of the company providing the app and the corresponding messenger service. In this particular case, it appears to have addressed a basic need for security among the test subjects. This may not be directly transferable to other apps. However, such "unique selling prepositions" should be particularly highlighted and communicated via the other elements. This is especially important from a market segmentation perspective because for one of the groups, the location of the server was the main influencer in the ultimate purchase decision.

The elements not yet mentioned at this point (app icon, app name, descriptive text, screenshots) should by no means be neglected during the course of marketing activities. From a mass market perspective these have a smaller overall influence on the customer's purchase decision and only have a limited ability to set the product apart from the competition. That being said, the segmented markets show that these elements have a greater influence over some of the groups. Accordingly, such elements must indeed be well designed, in order to convince a customer to purchase or to use the app. This is especially true when marketing to desired market segments. The descriptive text and the app name, for example, are nevertheless crucial for the app store's search algorithms to enable the mobile application to be found at all. Whether the app name is easy to remember is another factor that plays an important role in the selection process and in word-of-mouth propaganda.

Furthermore, it can be expected that in a perfect world, a killer app would be created and launched in the app store. As soon as it is launched, all potential users would be exposed to it and have the opportunity to download it and thus provide ratings which will promote further usage. However, generally speaking the app market is not a "field of dreams" and just because an app is built it does not mean "they" will come. As originally expected, there are different homogenous segments with very specific preferences with regards to the various app elements. Accordingly, effectively targeting the appropriate market segment can not only increase awareness and potential downloads, but also increase the chance that the app meets the user's needs and interests, which will result in higher ratings. As discussed earlier, outside of placing an app in the appropriate category, app stores do not offer the ability, via their platform, actively market to specific market segments. Thus, this study shows the need for such a tool as developers and marketers looking to reach these segments are currently forced to use external channels.

VII. Conclusions

This study has revealed some empirically based recommendations on how to align the elements of the app presentation in app stores to customer preferences. The results of the CBC analysis showed four main attributes of importance. While developers and marketers can influence two of the attributes the other two are a result of feedback from other users. While these four elements had the greatest over all influence over a user's ultimate purchase decision, the results of the LC analysis showed that different user segments have very different preferences and needs. While one group was very heavily influenced by price another was influenced by server location. This indicates that while the overall trend is to offer applications that are free (not counting for in app purchase options) there are still those that are willing to pay a premium for quality. Accordingly, appropriate market segmentation can help developers better reach their intended market and stand out in the vast sea of applications.

The findings, however, refer to a rather small and not representative sample. Moreover, the generalizability of the study is limited due to the fact that here just one single, specific application was investigated, using the example of select design elements of the Apple App Store. More detailed studies in different application domains and with regard to different app stores will be necessary in order to verify the validity of the findings derived in this study.

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