Investigating the efficacy of persuasive strategies on promoting fair recommendations

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Abstract

Fairness in recommender systems has gained lots of attention, considering provider and system objectives along with end-user satisfaction. However, often there are trade-offs between the objectives of different stakeholders. Music recommender systems suffer from popularity bias, meaning that songs from famous artists are widely recommended; in contrast, new artists on the same platform struggle to attract listeners. However, less popular providers might not satisfy users as much as widely-known providers; therefore, user satisfaction might decrease significantly. Consequently, there is a need to explore methods to promote recommendations from less-known providers. Previous studies have shown that explanations and persuasive explanations are beneficial for increasing user acceptance of recommended items. However, there has been little work investigating explanations for a fairness objective. This research is focused on the effect of persuasive strategies for promoting items included for the recommender's fairness objective in a music platform, highlighting which persuasive strategies can be used to create influential persuasive explanations. Results show empirical evidence of higher user satisfaction for the items accompanied by explanations. The findings of this thesis could guide the user interface design of multi-stakeholder recommender systems leading to better user satisfaction. Moreover, the impact of different demographic features and personalities on the ratings of songs from new artists is explored. Based on our results, users with different demographic characteristics and personalities are receptive to distinctive persuasive messages. This information provides a better understanding of the participants' behaviour, leading to personalized guidelines for designing persuasive fair music recommender systems. Furthermore, users' perception of persuasive strategies that they are susceptible to is compared with the actual persuasive strategies that the users were influenced by based on the rating users provided to the songs from new artists and persuasive messages individually. The comparison of the ratings yielded that users correctly identified influential and uninfluential persuasive messages with 38.25% accuracy. *Scarcity* was the most underestimated method; the users' perceived persuasiveness of this method was very low. However, the ratings of songs from new artists showed that this method affected users' ratings. This result shows that personalizing persuasive strategies solely based on the users' opinions about their receptiveness to the persuasive strategies might not reflect the true power of persuasion, at least in music recommendation.

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Dedication

To the innocent souls who lost their lives in the attack on flight PS752.

Contents

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List of Abbreviations

ANOVA	Analysis of Variance
LOF	List of Figures
LOT	List of Tables
OCEAN	Openness, Conscientiousness, Extroversion, Agreeableness, Neuroticism
PT	Persuasive Technology
SEM	Structural Equation Modeling
STD	Standard Deviation

1 Introduction

Nowadays, recommender systems have become an essential component of daily tasks because finding the most relevant information from the abundant amount of data available is laborious. Music recommenders are widely-used with platforms such as Spotify[1], and YouTube Music[2]. These platforms facilitate an easier way for the new artists to be exposed to listeners and present relevant playlists based on the listener's preference. However, the music industry is a superstar economy [74]. A minimal fraction of the artists and works accounts for a disproportionately large share of all revenues. Famous artists utilize high-end music production facilities to produce higher-quality songs and employ marketing strategies to promote their songs. Therefore, these popular artists become even more famous; nonetheless, new artists on the same platform struggle to monetize their music. Additionally, these recommender systems suffer from popularity bias, meaning that popular songs receive lots of exposure while less popular songs are under-represented, exaggerating the superstar effect [2].

1.1 Motivation

Most recommender systems are mainly optimized for maximizing end-user satisfaction; however, there are other stakeholders in the systems, and their intentions should also be taken into account for the recommendation. Burke et al. divided stakeholders of the given recommendation into consumers(who receive the recommendation), providers(who stand behind recommendation objects), the system(who create the recommendations) [15]. A multi-stakeholder recommender system considers all stakeholders' interests for generating a recommendation.

In music platforms, the consumers are the listeners, and the providers are the artists publishing their music. The interest of both listeners and artists should be taken into account for creating recommendations. From the artists' perspective, all artists with various popularity ranges should be treated the same by the recommender instead of the existing popularity bias. In a recent study, Mehrotra et al. developed a fairness-aware music recommender to recommend music from artists with a wide range of popularity [53]. Their findings showed that users' satisfaction is negatively impacted by content recommended for fairness. This outcome is predictable due to the ambiguity effect [25]. The ambiguity effect is a cognitive bias that indicates that a lack of information influences decision-making; hence people tend to choose the options with familiar

[1] https://www.spotify.com/
[2] https://music.youtube.com/

outcome. In a music context, listeners choose to listen to well-known artists that they already know instead of giving a chance to new artists. Consequently, when the music recommender suggests playlists with artists with various popularity, user satisfaction decreases significantly. Therefore, researchers need to explore methods to promote fair recommendations more persuasively to alleviate user dissatisfaction.

1.2 Research Problem

Research in explainable recommendations focuses on providing intuitive explanations for the recommendations to assist users in deciding whether an item is related to them. Herlocker et al. concluded that supplementing recommendations with explanations can improve the acceptance and adoption of the recommended items [32]. Furthermore, the explanations can be augmented with Cialdini's influence strategies to enhance the persuasiveness of recommendations. Gkika et al.'s experiment showed that user acceptance of a recommended item improves when supplemented by a persuasive explanation [30]. Consequently, this thesis investigates the effect of Cialdini's influence(persuasive) strategies on promoting new artists in a music platform that presents songs from both well-known and little-known artists [21]. It explores whether user satisfaction increases when informed about the rationale behind less related recommendations from new artists in a persuasive approach.

From a different perspective, in recent studies, personalized persuasion methods were introduced that mostly build upon users' self-report of their receptiveness to the persuasive strategies. However, how reliable are these self-reports? These studies make use of perceived persuasiveness because assessing the actual effectiveness of a persuasive strategy is difficult [69]. Therefore, in this thesis, we compared the persuasive strategies that users were shown to be receptive to during our study to with the strategies that were perceived as persuasive by the users (judged by the ratings they gave them at the end of the study).

1.3 Thesis structure

This thesis is organized as follows: Chapter 2: presents the background and literature review about persuasive technologies. Also, it provides background about multi-stakeholder recommendations and explainable recommendations. Chapter 3: discusses the user study conducted to examine the efficacy of persuasive strategies on promoting fair recommendations in a music platform. Chapter 4: analyzes the findings of Chapter 3, thoroughly analyzing the outcome of the study. Chapter 5: concludes with the main points of this research, elaborating on the contributions and future work.

2 Literature Survey

This chapter presents the research background and prior research in a conjuncture between multi-stakeholder recommendation, explainable recommendation and persuasive strategies. Section 2.1 describes the concepts in the fairness-aware and multi-stakeholder recommendation. Section 2.2 explains the background in the explainable recommendation. Section 2.3 presents an overview of persuasion concepts.

2.1 Fairness & Multi-stakeholder Recommendation

Recommender systems are now intertwined into different aspects of daily tasks, raising concerns about whether every individual and group is treated equally and exposed to benefits and harms fairly. Recommender systems provide recommendations based on past user preferences, targeting to predict user interest accurately. There are four main categories of recommendation based on filtering the recommended items from all available items: collaborative, content-based, knowledge-based and hybrid filtering methods [35]. Recommender systems using collaborative filtering technique propose recommendations based on choices of users who are similar to the current user. These similarities are calculated based on the recent interaction of these users with the recommended items. Content-based recommenders suggest items using semantic analysis of features of previously chosen or rated items by the user, from which the user's interests are inferred. The knowledge-based filtering technique makes use of users' similarities in a specific domain and recommends the items that users with close characteristics have preferred. Social recommender systems recommend items that friends or contacts of the user have liked. Hybrid recommender systems combine the above recommenders, taking the aspects mentioned above into the recommendation algorithm to overcome the limitation of one method with the advantage of other algorithms.

Most recommender systems focus solely on the end-user and optimize the system's objective to maximize user satisfaction with the recommended items. Nonetheless, the end-users are not the only stakeholder of the system. Therefore, in recent years, protecting the interest of other stakeholders in such systems has gained attention [4]. Burke et al. categorized the system's stakeholders into three groups [15, 1]:

- consumers: who receive the recommendations.
- providers: whose entities supply the recommended items.
- system: which creates the recommendations.

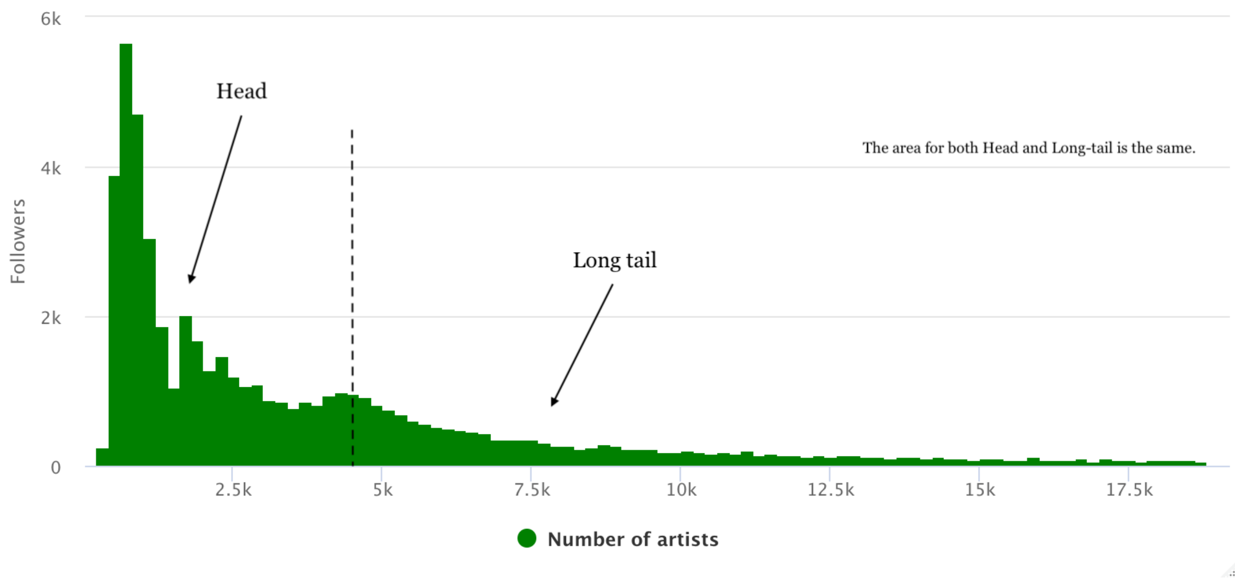


Figure 2.1: Artists Followers Distribution on Spotify

2.1.1 Popularity Bias in Recommender Systems

Research has shown that recommender systems typically suffer from popularity bias; popular items are recommended recurrently, leading to the majority of less known items being under-represented [11]. The collaborative filtering approach contributes to this bias as it is based on social similarities inherently [18]. Long tail items come from the region of the distribution that has occurrences far away from the "head" or central part of the distribution as shown in Figure 2.1. The long-tail artists on a music recommender are not as popular or even new in the system with a fewer number of ratings. Popular items are good recommendations as they have a higher probability of being familiar to the users. In contrast, the long-tail items are typically not recommended, leading to low exposure of such items, leading to no chance to become popular [70]. Subsequently, this popularity bias leads to treating the Providers of the recommender unfairly, leaving fewer opportunities for the new Providers to become well-known. Abdollahpouri et al. research in music recommendation showed that not only various artists with different levels of popularity are not treated the same by the recommender, but also the recommender system itself is exaggerating this bias [2].

One argument here is that users might be only interested in the popular items. However, this unfairness also exists between users of the recommender system. Abdollahpouri et al. defined unfairness for users as the accuracy difference for recommended items between different users. Some groups of users receive proper related recommendations based on their preference, but some groups receive unrelated recommendations. Their experiment concluded that the accuracy of the recommendations is related to the interest of the user in popular items, meaning that users who do not like well-known items are treated differently by the recommender [6]. Kowald et al. also presented the same discrimination in the music recommendation domain [43].

2.1.2 Fairness-aware Recommendation

Researchers have investigated methods to consider the objectives of different groups in recommender systems such that every group experience fair benefit and/or harm from the system and determined guidelines to incorporate fairness into these systems to be practical for the users. Recent research in this area is focused on four different approaches:

Fair division of resources by diversifying the recommendations: Levy et al. introduced a method to overcome popularity bias by diversifying the recommendations and recommending items from the long-tail distribution [47]. For this purpose, firstly, the pool of artists from the long-tail was created from the artists who had less than 10,000 reach on the Last.fm platform. When the user requests a recommendation, the similarities between the user's listening history and the artists from the long-tail pool were computed. Then, the most relevant artists to the user's listening history were extracted, and a playlist was provided with the songs from these long-tail artists. This method is used for reducing the popularity bias in a set of recommendations. Abebe et al. introduced a model to share the resources between neighbours so that no neighbour would envy the resources obtained by the other agents [7]. They mapped the relationship between agents as a social network for sharing the resources and identified the graphs with a protocol for computing locally envy-free allocations.

Fairness-aware regularization by constraining the recommender with a fairness objective: Kamishima et al., in a study in 2014, designed a model to correct the popularity bias by removing specified features from the predictors of the recommender based on a viewpoint selected by the user because these features convey sensitive information that might create a bias for the recommender. For instance, if the user has no interest in a popular item as their viewpoint, the recommender is capable of recommending less popular items to the user [37]. Unlike the previous approach, this method reduces the popularity bias in a single recommendation. However, this regularization approach is limited in handling multiple fairness objectives. Additionally, features might also be correlated. After removing the chosen feature, the remaining features might still contribute to the popularity bias due to its high correlation with the removed feature. Therefore, Yao et al. investigated the unfairness in collaborative-filtering recommendations using matrix factorization which is caused by the population imbalance in the data and observation bias. Observation bias is a bias created by the feedback loop in the data, meaning a specific user that is never exposed to an item would not provide ratings on the item, and the recommender can not learn about the user preference in this situation. To fix this unfairness, five new fairness objectives were proposed that could be utilized in the matrix factorization algorithm as penalties to reduce the unfairness. Unfortunately, this method only factors for user fairness objective and would not perform well in a sparsed data space [88].

Prediction models for individual fairness: Kamishima et al., in a study in 2016, designed a generative model to provide recommendations independent of specific characteristics. For instance, in a job applicant recommender, the recommendations should be independent of applicants' demographic information [38]. This model provided more flexibility for various information types than the regularization approach in their 2014 study. Burke et al. investigated a recommendation approach that considers personalization and fairness objectives simultaneously through a balanced neighbourhood mechanism. This method utilized a collaborative filtering recommender, in which the recommendations are generated from a balanced neighbourhood. Balanced in this context means that the number of neighbours concerning the accuracy objective and the fairness objective in the neighbourhood is equal. Then, they applied sparse linear methods to obtain a balanced neighbourhood for each user. The sparse linear method generalizes the item-based recommendation by learning a regression coefficient from the user-item pairs [59]. Burke et al. used this sparse linear method for creating the recommendation and added a balanced neighbourhood objective to the regularization function so that the recommender takes both accuracy objective and fairness objective in generating the recommendations [16]. Thus, this method lacks the ability to reflect the fairness objective of both consumer and provider simultaneously.

From a different point of view, Farnadi et al. researched a hybrid recommender that incorporated content-based, collaborative-based and demographic-based filtering approaches with also minimizing observation bias and population imbalance in the data. However, this model was not tested in a sparse data space which is the case in most real-world recommender systems [26]. Mehrotra et al. thoroughly studied provider-fairness and consumer-relevance and their relation with end-user satisfaction. Their results indicated that user satisfaction is higher for the recommender optimized for a guaranteed relevance to the user preference. Additionally, the recommender solely optimized for provider-fairness severely impacts user satisfaction. Overall the adaptive policy that tunes the number of fair recommendations based on the user's affinity for fairness was the middle ground without severely damaging user satisfaction and providing a certain level of fairness [53].

Fairness in rankings: Abdollahpouri et al. presented a regularization-based framework for a learning-to-rank algorithm with the objective of increasing the coverage of the items from the long-tail [3]. This regularization parameter is defined to be minimized when the distribution of the recommendations is fair. Fairness in this recommender system was defined as when half of the recommended list is from the short-tail items, and half is from the medium-tail to long-tail items. Their method offered a tunable mechanism to control the trade-off between coverage of the long-tail and the accuracy of the recommender. Their results showed that this method improved the coverage of the long-tail items without substantially degrading the recommender's accuracy. However, this method has two shortcomings: firstly, some users might not be willing to encounter long-tail items, and this preference could not be reflected in this method. Secondly, the long-tail objective of this system can only be encoded as the latent factor, so this method can only be used in factorization models. In an extension of the Abdollahpouri et al. [3] regularization method, Liu et al. [48] introduced a personalized fairness-aware re-ranking algorithm with the personalization being defined as users' preference in receiving diverse recommendations from providers with different levels of popularity. Fairness in their system was described as facilitating providers to reach all consumer groups. Their method consisted of a term for maintaining a certain level of accuracy and an additional term to account for the diversity of the providers. Their results showed that the recommendations could be diversified without significantly damaging the system's accuracy.

From a different perspective, Biega et al. designed an algorithm that captures unfairness to the level of individual items to counter popularity bias in the recommender system. In this algorithm, amortized fairness is guaranteed in which attention is fairly distributed between the items. The algorithm shuffles the items with the same relevance so that all of the highly-relevant items have the chance to appear at the top of the ranking. Additionally, this method also maintains a certain level of quality. The results from this study also showed improved individual fairness for the items with high ranking quality simultaneously [14]. Nevertheless, this method did not focus on the personalized rankings of the items. In such systems, the relevancy for all of the items is known beforehand, which is not the case for most real-world applications. Beutel et al. introduced a pairwise fairness metric and designed a recommender system optimizing for this metric. Fairness in this method was defined as the likelihood of a clicked item being ranked above another relevant unclicked items, being the same across different groups. This model can be utilized to see whether a group faces any unfairness in the recommendations [13].

Abdollahpouri et al., in a 2019 study, introduced a post-processing approach to mitigate popularity bias in the recommendations. This method builds up from the generated recommendation. It produced a new re-ranked list by optimizing the system's accuracy and diversifying the recommendations by adding items from the long-tail. Their results showed that this post-processing approach could be utilized to include items from the long-tail without diminishing the system's accuracy [5]. From the user perspective, Sonboli et al. [80] researched the user perspectives of fairness-aware recommender systems and techniques for enhancing their transparency by interviewing users about what fairness means to them. Their study concluded that users prefer to be educated about the rationale behind the fair recommendations, especially with an explanation specific to each recommendation.

2.2 Explainable Recommendation

Prior research in recommender systems has shown that accompanying recommendations with explanations can help users understand the rationale behind recommendations and improve adoption, perceived quality and effectiveness of the recommendations [32]. Herlocker et al. conducted a study in which the users consulted the MovieLens recommender for 12 movie recommendations with different explanations and rated each recommendation as to the effectiveness of the explanation. They discovered that the relevant item explanation is more intuitive for the user to understand compared to the relevant user explanation. This difference is because the user might not know other users or trust the system showing the truth [32, 27]. Tintarev and Masthoff et al. designed a study to investigate the role of explanations in recommender systems. They classified the goals of the explanations into seven groups: transparency, scrutability, trust, effectiveness, persuasiveness, efficiency, and satisfaction [84]. These goals have different relationships with each other, so optimizing for one of these objectives might decrease or increase the other goal. For instance, increasing

Table 2.1: Explanation objectives [84]

Objective	Goal
Effectiveness	Help users make good decisions
Efficiency	Help users make decisions faster
Persuasiveness	Convince users to try or buy
Satisfaction	Increase the ease of use or enjoyment
Scrutability	Allow users to tell the system it is wrong
Transparency	Explain how the system works
Trust	Increase users' confidence in the system

the system's transparency might increase users' trust in the system depending on whether users believe the system is working as being explained or not. Table 2.1 describes different explanation goals. Their result also showed that personalizing the explanations leads to an increase in user satisfaction; however, it harmed the effectiveness of the recommendations [84].

Gedikli et al. researched the effect of 10 different visual explanations in different dimensions. These explanations are as follows: *histogram with showing grouping such as using ratings for grouping*, *Neighbours ratings histogram*, *Table of neighbours rating*, *Percent confidence based on historical data*, *Number of neighbours*, *Overall percent rated 4+*, *Overall average ratings*, *Pie chart*, *Tag cloud of the features of the item*, and *Personalized tag cloud*. The outcome of their study showed that different explanations have different effects in different dimensions; for instance, they can contribute to the user perceived transparency of the system or help the user decide faster. Overall, the tag-based explanations were the most effective explanations, with the personalized tag-based explanation also enhancing the trustworthiness of the recommender. Moreover, they found a significant positive relationship between transparency and user satisfaction [29].

From a different perspective, Gkika and Lekakos et al. examined the persuasiveness of explanations in recommender systems, using Cialdini's persuasive strategies and concluded that all six principles enhanced users' perception of the recommended items, with *Authority* and *Social Influence* being the most effective methods for persuading users to interact with an item. Also, their results showed an increase in the adaption of the recommendation, meaning that a user is more prone to interact with an item that is accompanied by a persuasive explanation [30]. Ren et al. focused on the social aspect of recommender systems and introduced a social, collaborative viewpoint regression model. This recommender showed explanations for the items that trusted user friends had shared in the platform; then, it utilized sentiment analysis for extracting explanations from users' opinions, referenced as viewpoint. Therefore, the explanations in this recommender showed friends' opinions about an item to the user. This social recommender also contributes to preserving the users' privacy in the system as the opinions are not publically available, and a friendship should be accepted beforehand to show the opinions [72].

Kouki et al. introduced a hybrid explainable recommender with different data sources(user-based, item-

Table 2.2: Explanations [42]

Explanation Style	We recommend U2 because:
User-based	User Aren with whom you share similar tastes in artists, listens to U2.
Item-based	People who listen to your profile item AC/DC also listen to U2.
Content	U2 has similar tags as Beatles that is in your profile.
Social	Your friend Cindy likes U2.
Item popularity	U2 is a very popular in the last.fm database with 3.5 million listeners and 94 million playcounts.

based, content-based and social explanations) and different explanation formats(textual and visual explanations). Table 2.2 shows example explanations from their study. Their study indicated that the perceived persuasiveness of the explanations highly depends on the style of the explanation, with textual item-based and content-based explanations being more persuasive than the other explanation styles. Additionally, they investigated the relationship between the personality of the users and the persuasiveness of the explanations. They concluded that anxious users are more receptive to item-based explanations, but conscientious users are more receptive to popularity-based explanations [42].

Millecamp et al. thoroughly investigated the relation between explanations and user characteristics in a music recommender. In [55, 56] studies, they researched the effect of personal characteristics on the perception of the explanations. They divided the personal characteristics into three groups:

- Need for cognition: The Need for Cognition (NFC) is a psychological term that refers to a person's inclination to obtain, assess, and integrate various relevant sources of information to make sense of events.
- Musical sophistication: Musical sophistication is a psychometric concept encompassing musical abilities, expertise, accomplishments, and behaviours of either individual with/without musical training [57].
- Big Five Inventory Personalities [36]

In [55] study, they discovered that when individuals with lower levels of need for cognition prepared their playlist with explanations, they had more confidence in it than when they did not. In the second study [56] they found that users with high musical sophistication acquire significantly higher decision support from the explanations. Additionally, the user's Openness score and the interface influence the originality of music retrieved by users. Users with low openness discovered unique music with explanations. These studies [55, 56], along with Kouki et al.'s study [42], targetted the relation between perception of the explanations and the personality of the users but did not aim to design and evaluate a recommender that personalizes explanations. Therefore, Millecamp et al. researched the efficacy of personalized explanations for a music recommender based on different levels of the characteristics mentioned above [51]. They also introduced guidelines for designing a recommender system with personalized explanations. Their results revealed that all participants preferred explanations; however, displaying the explanations should be optional for the users with less need for cognition. Additionally, simple explanations that do not require domain expertise were more effective for people with minimal musical sophistication.

By introducing model-based recommender systems such as factorization machines and deep learning models, providing explanations for the recommendations gets more challenging as the models extract latent features, and the exact factors influential in the recommendation algorithm could not be precisely determined. Zhang et al. introduced a model-based recommender that accompanies the recommendations with the explanations. The model utilized a matrix factorization method and provided explanations based on the features of the recommended item and the user's interest in the feature. The outcome of their study showed an improvement in the persuasiveness of the recommendations [89]. In model design, there is a trade-off between the explainability and the accuracy of the system; complex recommenders such as factorization machines have better accuracies, but with the cost of losing explainability of the recommender [73]. In contrast, Zhang et al.'s study was one of the few studies that showed that the explainability and accuracy might not have a conflict with each other.

Seo et al. presented the Interpretable Convolutional Neural Network, a deep convolutional neural network that provided explanations by describing the recommended item features. They applied two neural networks, one for determining the semantic meaning of the reviews on the platform and one for finding out the user's preference/ item features from the reviews. Combining these two neural networks led to meaningful explanations showing a more interpretable representation of the latent features [76]. Ai et al. introduced a knowledge graph-based explainable recommender that learns explanations for the relations between users and items such as *the item belongs to category.* The underlying recommender system in their study was a simple content-based recommender suggesting items similar to the user's purchase history. The explanation for the recommendation could be extracted from the shortest path from the user to the item, presenting the explanation for the relations between users, items or user-items along the path [10].

From a different point of view, Cheng and Shen et al. introduced a post-hoc explainable recommender, which is a model-agnostic approach. This method focused on influence analysis by finding the model's most influential training data that led to each recommendation; afterwards, an explanation was provided based on the neighbours of the traced-back training data. Their experiments with the real-world dataset not only showed the efficacy and efficiency of the proposed post-hoc model but also the generated explanations were helping users decide faster. Though the explanations may not exactly replicate the process that generated the recommendations, they offer the benefit of being adaptable to a variety of recommendation models [19].

2.3 Persuasive Recommendation

Persuasion is an attempt to change behaviours or attitudes or both, without coercion, and Persuasive technologies(PT) use technology to influence the behaviours or attitudes of the users [28]. Various persuasion techniques have been proposed, such as the 40 *persuasive strategies* introduced by Fogg [28], the six *principles of influence* by Cialdini (which is seven now)[21], or the 64 *compliance-gaining strategies* by Kellermann and Cole [40]. This thesis utilizes Cialdini's persuasive strategies because they are widely applicable and easy to implement. Cialdini's seven persuasive strategies are as follows [21]:

- *Reciprocity*: People are more likely to say yes to the people whom they owe. A demonstration of this strategy was studied by Strohmetz et al.. They investigated the influence of offering small gifts such as candies on customers tipping at the end of serving. They showed that with this simple trick, not only the amount of tips was increased; also, if the server offered personalized and unexpected gifts, the amount of tips would increase even more [82].

- *Scarcity*: People want more of what they can have less of. This strategy is widely used on an eCommerce website by showing the number of seats left on the airplane for flight tickets or showing the count down about the length of the offer on Amazon website [1].

- *Authority*: People follow the authority of knowledgeable experts. Milgram et al. studied the reaction of individuals to the electric shocks, and the participants had different reactions toward a person wearing a white lab coat and an unseen individual. The participants reacted more respectfully to the individual wearing a lab coat as they look like a scholarly person and source of authority in this situation [54].

- *Commitment*: People like to be consistent with their past behaviour. Lokhorst et al. investigated the application of commitment strategy in the environmental domain. The study aimed to ask the users to put a wooden board on their lawn supporting the Drive Safely campaign. They discovered that the users who agreed to use a small postcard behind their window supporting Drive Safely campaign, were more willing to put a large sign on their lawn compared to the other group that did not make a smaller prior to this cause [49].

- *Liking*: People tend to say yes to the people they like, for example, people who are similar to them, people who complement them or people who cooperate with them toward a common goal. Maddux et al. researched the application of liking strategy in negotiation. In the study, the participants were divided into two groups: one group only negotiated with each other, but the other group got to know each other, found similarities between themselves, and then started negotiating. Their study showed that the first group's success rate of coming to an agreement was 55%, and the latter group was 90%. Therefore, the liking strategy influences our decision-making [50].

[1]https://www.amazon.com

- *Social Influence*: People tend to do what others do, especially when they are uncertain. Shang et al. studied the effectiveness of social influence strategy in promoting reusing towels in hotels. Their participants were divided into two groups; the first group of guests received a note regarding the environmental benefit of reusing the towels. The second group of guests received the same with extra info regarding that 75% of the guest before had reused the towels. The towel reuse difference between the two groups was 26%; therefore, the social influence strategy can be effective [77].

- *Unity*: The recently introduced strategy is Unity, which is the shared identity between the influencer and the influencee. Identity means the categories individuals categorize themselves as, such as race, affiliation, nationality. This strategy means that *we is the shared me*, therefore a member of the category, influences the confidence of other group members [20].

These strategies are based on the idea that different people are impacted differently; therefore, thre is no universally effective persuasive strategy. To identify the most effective strategies for the users, measuring the effectiveness of persuasive strategies is vital. O'Keefe et al. [69] discovered that the perceived persuasiveness was no better than tossing a coin in terms of estimating actual persuasiveness in the domain of communication studies. Additionally, measuring the actual effectiveness of a persuasive strategy is complicated for various reasons. Firstly, verifying the effectiveness of a behaviour change application requires additional information, mainly depending on the user reports, which are often not accurate. Moreover, due to confounding factors, determining effective persuasiveness is challenging. For instance, the user might get motivated by the intervention in a language learning app. However, other factors such as users' travel plans or even social life might affect their motivation [83]. Subsequently, most of the studies in the area of designing persuasive digital interventions are based on users' perceived effectiveness of the persuasive strategies.

2.3.1 Personalizing Persuasive Technology

Kaptein et al.[39] researched the efficacy of persuasive text messages on reducing snacking. They discovered that if the persuasive strategy is appropriately tailored for the user, this intervention effectively discourages the user from unhealthy behaviour. However, if the applied persuasive strategy does not fit the user, the intervention would not be effective and could lead instead to a strong adverse reaction to this intervention. Additionally, Kaptein et al. introduced a questionnaire *Susceptibility To Persuasion Scale(STPS)* to measure users' perceived effectiveness of persuasive strategies[39]. The results of our study, in the domain of fair music recommender systems, raise a question about the reliability of user-reported perceived persuasiveness of strategies.

Orji et al. introduce *LunchTime* as a game to promote healthy eating habits via persuasive strategies such as social comparison and reward. In *Lunchtime*, players choose from a list of food choices and get rewarded with points if they chose healthy options. Additionally, it provided a leaderboard for the users to compare themselves based on their points. Their results showed that this game was effective in behaviour change as the users reported that the game came to their mind when they were making food choices in the real world and made them reevaluate their food choices [62]. Orji et al. conducted another study in which they studied the effectiveness of persuasive strategies for different gamer types. Gamers in the study filled a survey reflecting on their perceived effectiveness of the persuasive strategies based on a storyboard describing the persuasive strategy for them. Then the persuasive profiles matching gamer types with effective persuasive strategies were extracted from the survey result and used afterwards to determine guidelines for designing persuasive games targeting a health goal [63], some of which have been shown to be very effective in an experimental persuasive system [61].

From another perspective, Oyibo et al. [67] conducted three studies on the relationship between receptiveness of persuasive strategies and users' backgrounds and personalities by extracting the users' persuasion profiles with STPS questionnaire [39]. The study on the relationship between Big-Five personality traits and Cialdini's persuasive strategies showed that the most reliable predictors of Cialdini's persuasive strategies are Conscientiousness, Agreeableness, and Openness. Neuroticism is the least reliable, predicting only Social Influence. They also discovered that none of the personality factors predict Scarcity among Canadians [67]. In another study, Oyibo et al. investigated the relationship between gender and the persuasion profile of Nigerians. They discovered that Nigerians are susceptible to all of Cialdini's persuasive strategies. Additionally, Commitment, Reciprocity, Authority, Liking, Consensus, and Scarcity were ranked from highest to lowest in terms of effectiveness. Gender plays a factor in Nigerians' responses, with males being more receptive to Commitment and Authority than females [65]. Oyibo et al. compared Canadians and Nigerians susceptibility to determine personality determinants of receptiveness of the persuasive strategies. The results demonstrated that Nigerians are more susceptible to all methods than Canadians, except the Commitment strategy. Authority and Scarcity, in particular, were proven to be the most effective on Nigerians. Reciprocity and Liking, on the other hand, were proven to be the most effective on Canadians [64]. In another study, Oyibo et al. designed a fitness application to discover the determinants of bodyweight exercise performance relating to behaviour modelling. Firstly, the study identifies user persuasion profiles based on a questionnaire and then creates personalized interventions to promote physical activity. The effectiveness of the interventions was measured from user-reported adherence to exercise. They discovered that the interventions effectively motivated users to exercise more and identified self-efficacy and social influence as the most decisive determinants of bodyweight exercise behaviour [66, 68].

Ciocarlan et al. [22] researched the actual persuasiveness of Cialdini's persuasive strategies by designing a game that included persuasive descriptions for the quests. The game was a text adventure game that contained several quests. The character helps the fictional characters inside each quest only once, and each quest accompanies a persuasive message with itself. They evaluated the effectiveness of a persuasive strategy in the order the quests were chosen. They discovered that different users are susceptible to distinct persuasive strategies, with reciprocity and liking being the most effective persuasive strategies. Their results also indicated that users' susceptibility to specific persuasive strategies stays the same over time.

2.3.2 Persuasive Technology for Recommendations

Gkika and Lekakos et al. [30] examined the persuasiveness of explanations in recommender systems, using Cialdini's persuasive strategies and concluded that all six principles influence users' perception of the recommended items. They conducted a study on a movie recommender and included persuasive messages with the recommendations. Their findings showed that adding a convincing explanation to recommendations close to users' tastes positively impacts their decision to accept or reject recommended products. Gkika et al.[30] further extended this study to examine the effect of personality on accepting the recommendations accompanying a persuasive textual explanation. In their study, the users were asked to rate the recommendations indicating whether the user would watch the recommended movie or not. The findings demonstrated that each of the six persuasive strategies positively influenced users' acceptance of suggestions. The most powerful persuasive strategies were Authority and Social Influence. Furthermore, their findings revealed that the users' personality influenced the efficiency of persuasive strategies [79].

Pilloni et al. [71] investigated the efficacy of persuasion in a health recommender system that aimed to identify the athletes who are losing motivation and immediately referred them to their coach with an explanation about the behaviour change in the athlete's behaviour. Additionally, their designed recommender system also recommended persuasive strategies to the coach to persuade the athlete to continue training.

Adaji et al. [8] researched the impact of Cialdini's persuasive strategies on eCommerce shoppers, promoting healthy food choices in an online food shopping game. The game recommended healthy products to the players and accompanied the recommendations with a persuasive message. Players were required to use the app for at least three rounds to have their reactions to the persuasive messages recorded. The authors divided the users into four categories depending on their shopping motivations: convenience shoppers, variety seekers, balanced buys, and store-oriented shoppers. Then, using pre-game and post-game surveys, the change in users' attitudes, intention, self-efficacy, and perceived product price were determined. Their findings reveal that persuasive principles affect shoppers depending on their reasons for shopping online.

2.3.3 User Personality

Personality traits and the scales to measure and quantify personality traits are thoroughly studied in psychology. One of the famous personality questionnaires is the *44-item inventory* [36] measuring an individual on the Big Five Factors of personality [31]. This model is the most widely accepted model of personality, and its comprehensiveness has been supported practically and theoretically [45, 23, 52]. The big five personality traits are Openness, Conscientiousness, Extroversion, Agreeableness and Neuroticism (OCEAN).

These five dimensions exhibit personality differences, in which each personality trait has several distinguishing qualities, or adjectives, that set it apart from others and its measured on a spectrum. The personality traits and the adjectives are described in Table 2.3 [36]. The Big Five (OCEAN) personality questionnaire is included in Appendix B.

Table 2.3: Big Five dimensions and related adjectives

Big Five Dimensions	Adjectives
Openness (vs. Closedness to experience)	curious, imaginative, artistic, wide interests, excitable, unconventional
Extroversion (vs. Introversion)	sociable, forceful, energetic, adventurous, enthusiastic, outgoing
Conscientious (vs. Lack of direction)	efficient, organized, not careless, thorough, not lazy, not impulsive
Agreeableness (vs. Antagonism)	forgiving, not demanding, warm, not stubborn, not show-off, sympathetic
Neuroticism (vs. Stable)	tense, irritable, not contend, shy, moody, not self-confident

2.4 Summary

Fairness in recommender systems has gained lots of attention considering provider and system objectives along with end-user satisfaction. However, often there are trade-offs between the objectives of different stakeholders. For instance, *fairness* for providers can be defined as ensuring the same exposure for all providers [15]. However, by ensuring fairness for providers and promoting less popular providers might not ensure the same satisfaction for users as much as widely-known providers. Consequently, there is a need to explore methods to promote recommendations from less-known providers more effectively, without compromising user satisfaction. Previous studies have shown that explanations and, specifically, persuasive explanations are beneficial for increasing user acceptance of recommended items. However, there has been little work investigating explanations for a fairness objective and specifically persuasive explanations, and personalization of persuasive explanations in the context of multi-stakeholder recommeder systems with a fairness objective. The next chapter presents the user study that I have conducted to examine the effect of explanations using persuasive strategies on promoting new artists on a music recommender platform.

3 Persuasive music recommender promoting new artists

Nowadays, online music recommenders are one of the primary sources of music streaming worldwide. Spotify is one of the popular streaming platforms with more than 355 million active listeners [81]. As countless tracks are published on these platforms daily, users rely on systems-recommended playlists and songs to find relevant artists to their taste of music. Nonetheless, music recommender systems suffer from popularity bias meaning that recommendations are skewed toward popular songs [43]. Therefore, new artists struggle to be exposed to listeners. Unfortunately, when the recommendation algorithms are designed to recommend songs from artists with various popularity, the user satisfaction rate drops drastically [53]. From a different perspective, recent studies have shown that when a recommendation is accompanied by an explanation, especially a persuasive explanation, user acceptance of the recommendations increases notably. That is why my research is focused on evaluating the effect of Cialdini's [21] persuasive strategies on promoting new artists on a music platform by recommending songs from users' favourite genres and supplement songs from new artists with persuasive phrases. The rest of this chapter is organized as follows: Section 3.1 explains the study methodology, and the process of data collection and analysis are presented in section 3.2.

3.1 User Study Methodology

Our user study followed the Goal, Question, Metric (GQM) framework of Basili for design and evaluation [17]. In this framework, the goals of the study are identified first. Secondly, the reflective questions regarding the goals are defined, and lastly, the measure for achieving the goal is selected. The main goals of this user study are:

- Assess the effectiveness of Cialdini's persuasive messages on promoting new artists.
- Assess the impact of different factors, namely: age, gender, culture, personality traits, on users' susceptibility to persuasive messages.
- Evaluate the relationship between users' personalities and different persuasion principles. The purpose of this evaluation is to provide guidelines for personalizing persuasive messages based on user personalities to increase users' acceptance of the recommendations.

3.1.1 Study Design

A within-subject study design is utilized in this study, meaning that the same person experiences all persuasive strategies. The study begins by requesting user consent for participation in the study, followed by questions about the user's demographic background and music taste by selecting two genres from a list of 8 available genres (Appendix A). Afterwards, the participant is shown a paragraph about the superstar economy in the music industry and then asked to rate how important promoting new artists is for them on a 0-10 Likert scale. The following paragraph exhibits the information on the superstar economy from the preliminary questionnaire.

"*The music industry is a Superstar economy, a minimal share of the total artists and works account for a disproportionately large share of all revenues. For instance, the top 1% of famous artists account for 77% of all artists recorded music income. Famous artists have lots of attention, and their new songs are widely recommended to users regardless of their quality. In contrast, many new talented artists do not find any chance to be heard. Therefore, this study aims to provide new artists with an opportunity by including fair recommendations in our music recommender* [58]."

The mock-up recommender provides six playlists, suggesting three playlists for each genre selected by the user at the beginning of the study. Each playlist holds four songs from famous artists and four songs from new little-known artists, except one of the playlists that solely holds songs from little-known artists. The selected new little-known artists did not have any songs with more than 1000 streams on Spotify. In our interface, songs from new artists are accompanied by persuasive phrases based on Cialdini's persuasive strategies shown in Table 3.1. These principles were selected from the set of many possible persuasive strategies discussed in Chapter 2, because they are domain-independent and widely used in literature. According to Gkika [30] these principles have been proven to be universal persuasive approaches and provide a solid foundation for examining the persuasive power of messages in recommender systems as additional cues. Participants rated each playlist based on three criteria, overall satisfaction, popular songs and songs from new artists using a Likert scale from 1 to 5, and answered the Big Five Personality test questions [36] while rating. Figure 3.1, Figure 3.2 and Figure 3.3 show an overview of the interface. The Big Five (OCEAN) personality questionnaire is included in Appendix B. From now on, for brevity, I will use the terms *persuasive message* and *description* to denote the specific message under a song that implements a particular persuasive strategy, one of those listed in Table 3.1. To evaluate whether mentioning the song is from a new artist influences the effectiveness of persuasive messages, two persuasive messages (Scarcity and Social Influence) have two implementations, one claiming the song is from a new artist and one without saying so. Moreover, simple explanation for the recommended song from new artist is referenced as *Purpose*.

To assess the effect of persuasive messages on ratings of songs from new artists, I have chosen different configurations for the playlists. The mock-up recommender presents three playlists for each of the 2 genres selected by the participant, 6 in total. Four of the playlists (Number 2, 4, 5 and 6) contain a mix of popular songs and songs from new artists, where the unpopular (new artists) songs have a persuasive message

Table 3.1: Songs from New Artists' Persuasive Messages

Persuasive Strategy	Message
Authority	Experts have recommended this new little-known artist.
Commitment	This song is included because you agreed to have fair recommendations.
Empathy	75% of new artists don't find a chance to become famous despite being good.
Liking	Drake has suggested this new artist providing a chance to become popular.
Purpose	This song is included to give new artists a chance to be listened to.
Reciprocity	Thanks for using our fair recommender.
Scarcity without mentioning new artists	This song is only available for a limited time.
Scarcity with mentioning new artists	This song is only available for a limited time to promote this new artist.
Social Influence without mentioning new artists	80% of our users so far have listened to this song.
Social Influence with mentioning new artist	80% of our users so far have listened to this song from this new artist.

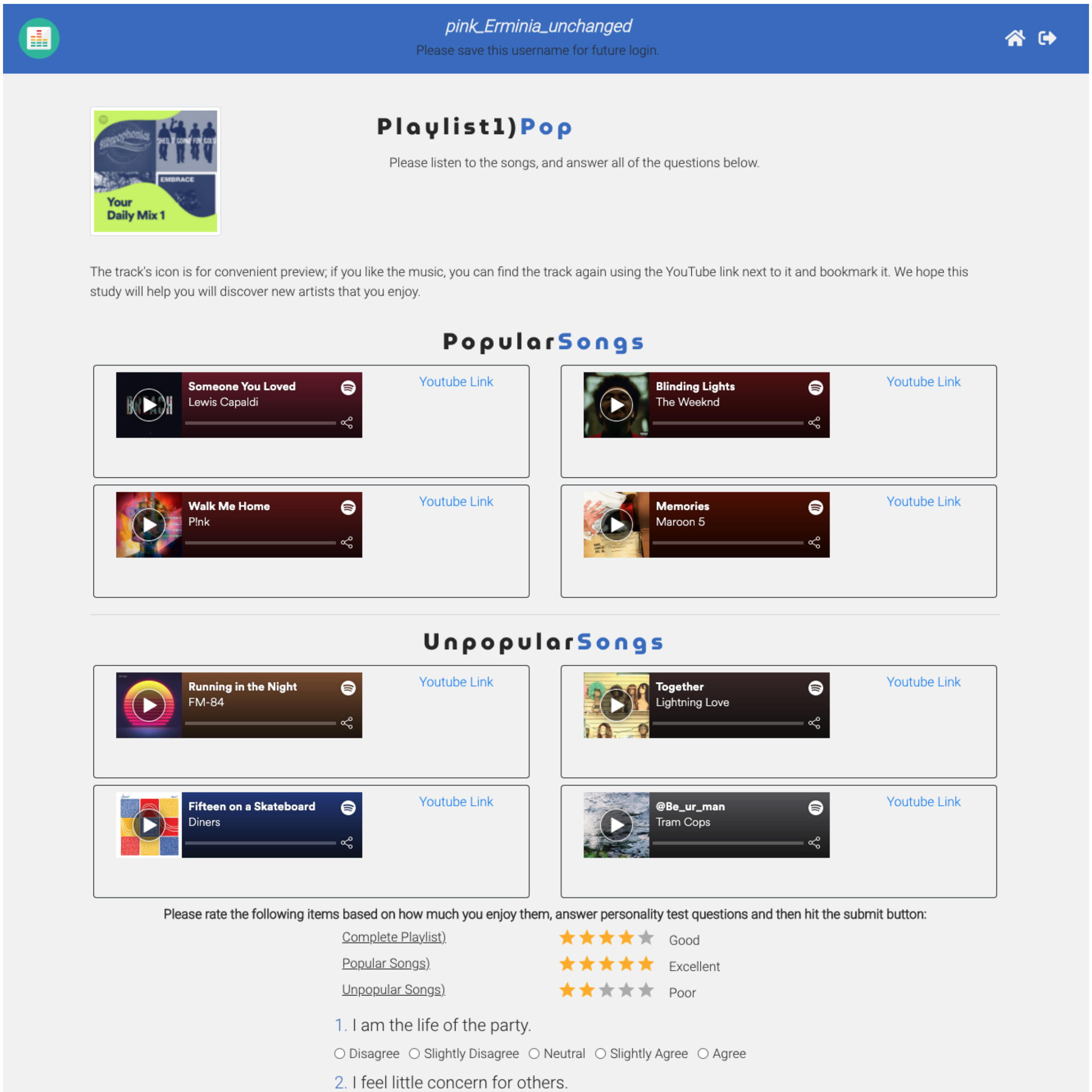


Figure 3.1: Playlist without persuasive messages

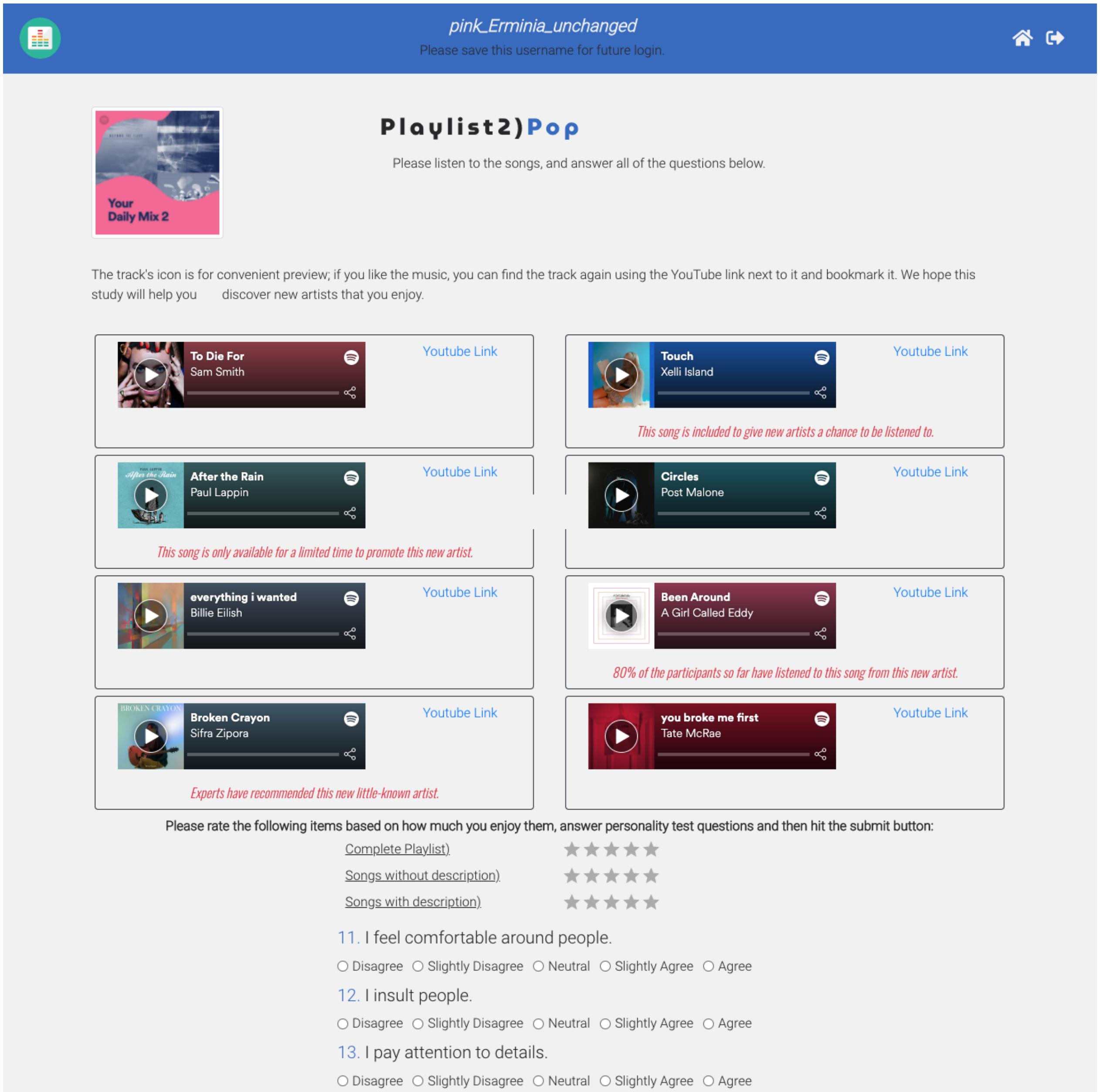


Figure 3.2: Playlist with persuasive messages

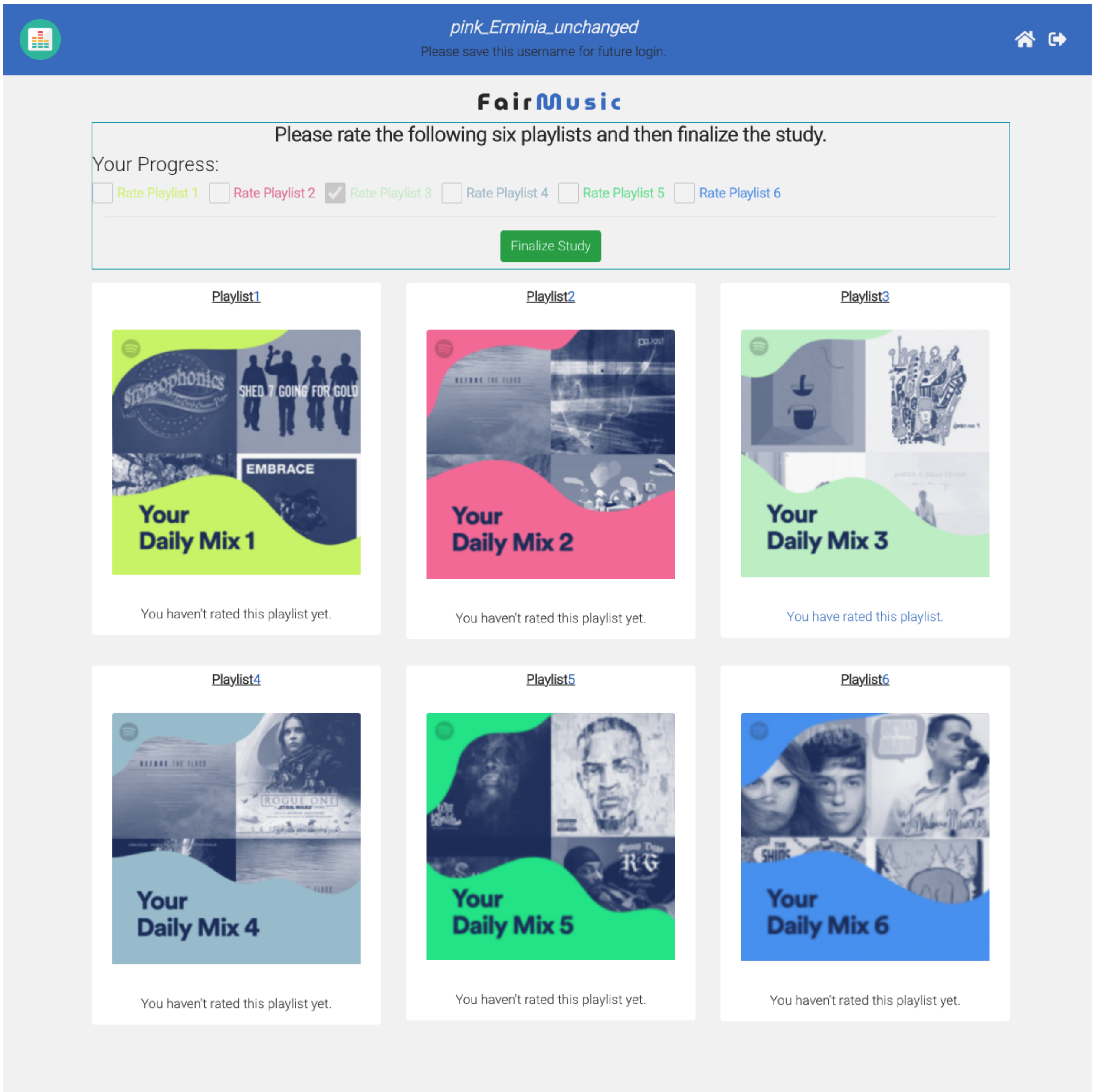


Figure 3.3: Study progress overview

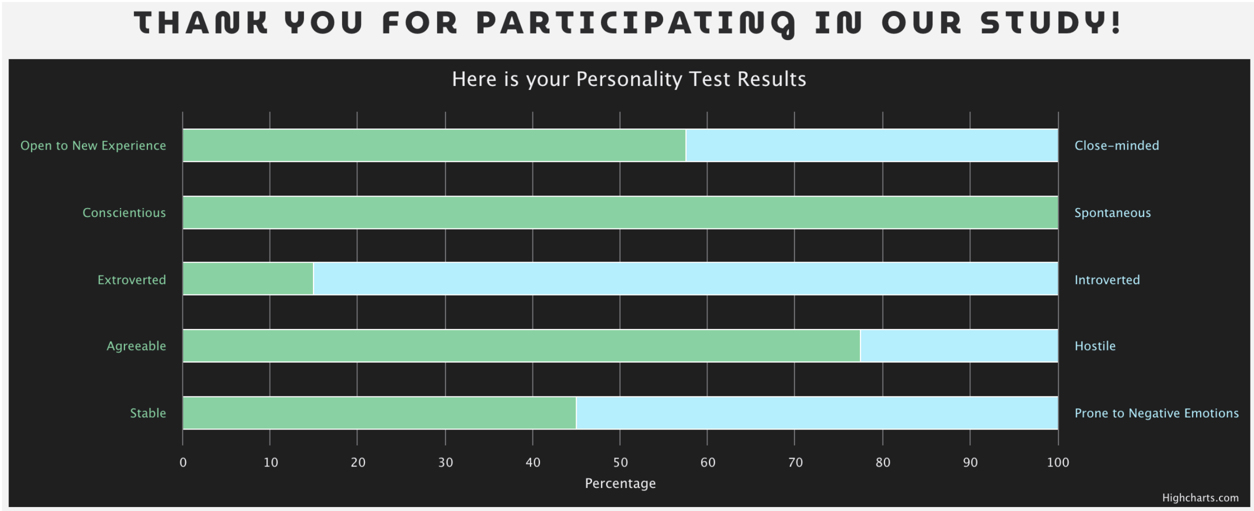


Figure 3.4: Personality Test Result

underneath the song title, based on one of Cialdini's influence principles [21]. The persuasive messages are as shown in Table 3.1. Two of the playlists are different and used as *control* conditions. Playlist 1 contains a mix of popular and unpopular songs but without persuasive messages to evaluate how users rate songs from new artists without any persuasive message by only knowing the song is from a new artist. Playlist 3 contains only unpopular songs from new artists, some with persuasive messages and some without, to assess whether users rate songs without messages higher than ones accompanying a persuasive message(although users only rate songs from new artists in this playlist). Each of the ten designed persuasive messages was displayed twice in different playlists throughout the study.

After rating all six playlists, the participant answered a questionnaire about trust and usefulness of this system and rates each persuasive message based on its perceived influence on their rating, which can be viewed in Appendix C. After answering this questionnaire, the result of the personality test was presented to the participant as shown in Figure 3.4.

3.1.2 Ethics Approval

For this study to be compliant with the behavioural research ethical standards, an application was submitted to the Research Ethics Board (REB) at the University of Saskatchewan. The REB ensures that this research adheres to the highest ethical standards and that participants who serve as research subjects are adequately protected. The study received behavioural ethics approval from the University of Saskatchewan REB under Nr. Beh-2260. The certificate of approval is included in Appendix D.

3.1.3 Participants

All participants in the study were recruited through university announcement board, newsletters and social media posts in January 2021. The study took about 30 minutes to complete, but the participants could complete the study in as many sessions as they wished and were rewarded with their personality test results in the end. A total of 463 participants started the study, but only 211 participants completed the study.

3.2 Data Collection

3.2.1 Data Filtering

To check our data's reliability, first, the participants who did not complete the study were removed, reducing the data size to 211 participants. Then, the personality data and rating results were checked for outliers. Checking for outliers utilized box-plot method, describing the data as an outlier if it is $1.5 * IQR$ below the first quartile or above the third quartile, where IQR is defined as the difference between third and first quartile [87]. The comparison between quartiles was checked for each Big Five (OCEAN) personality to remove the outliers. Six outlier participants were removed from the data because their personality results were improbable compared to the other participants, and interpreting the personality results of these participants showed inconsistency between their personalities results. For instance, one participant always chose the last choice in the personality questionnaire, which is improbable. Additionally, two more outlier participants were removed because their rating of the system was far from other observed data; they always chose five stars for all rating criteria. Therefore, the analysis was conducted using only 205 participants.

3.2.2 Participants' Demographic Information

Our participants included 66% women, 32% men. 55% of our participants were between 18-24, 32% between 25-34, 7% between 35-44, 3% between 45-54, 2% older than 55 and 1% younger than 17 years old. For the country where participants were born, most users were born in America, Asia and Europe, 60%, 30%, and 5%, respectively. Figure 3.5 shows participants' demographic information ratio. The users were asked about the importance of promoting new artists after reading the superstar economy paragraph on a scale from 0 to 10, and the average was 6.8 with a standard deviation of 2.0. Figure 3.6 exhibits the summary of personality results. The majority of our participants are agreeable and open, which is expected as they have accepted participating in such a study in the first place, with no financial incentive.

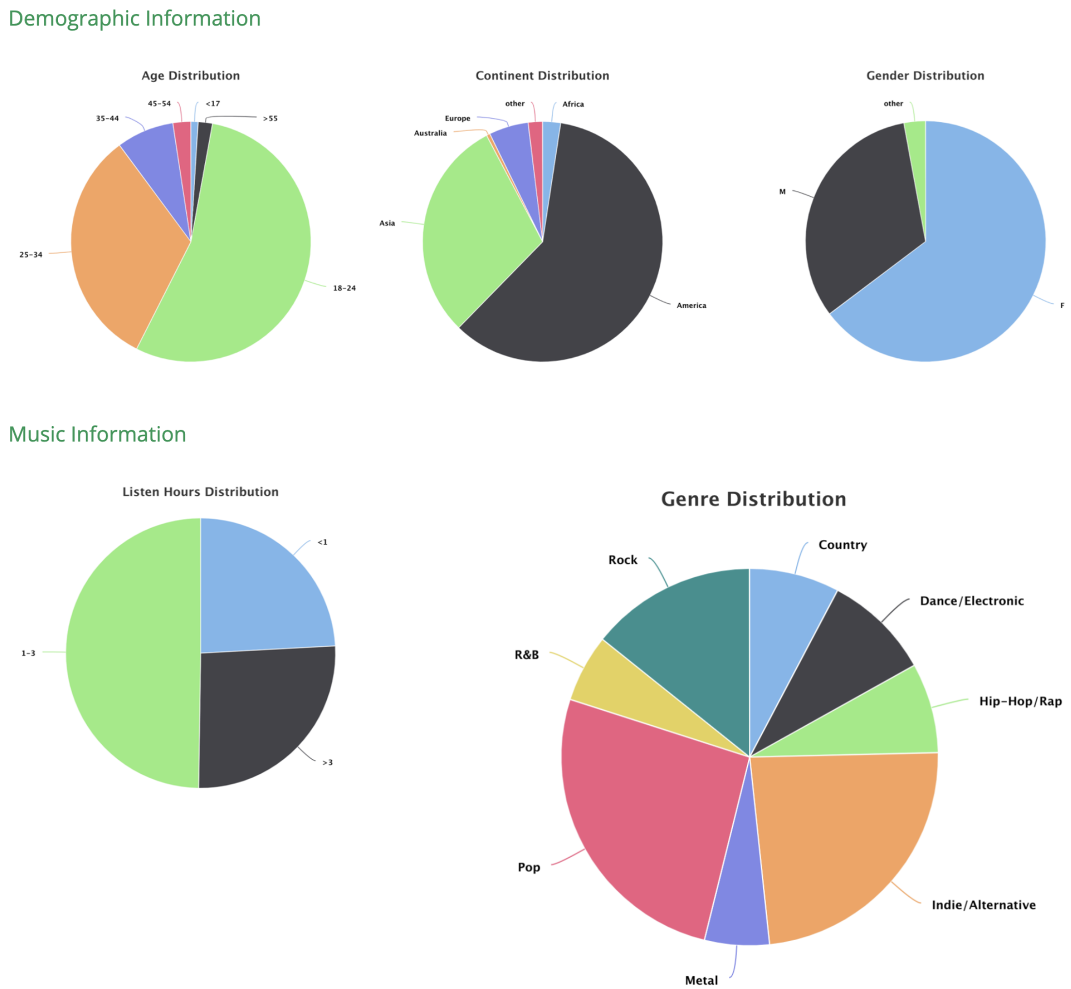


Figure 3.5: Overview of participants demographic information distribution

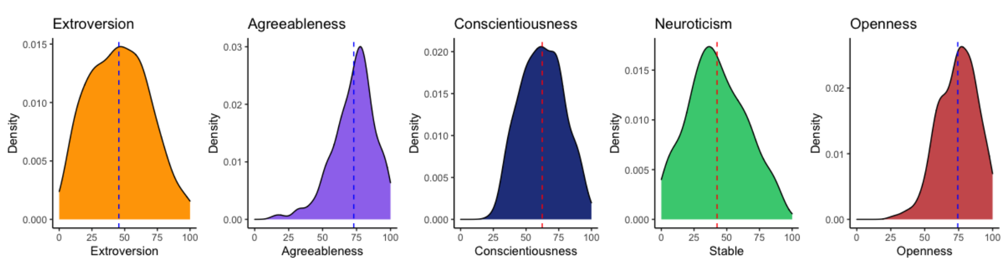


Figure 3.6: Participants' personalities distribution

4 Results and Interpretation

In this section, the main findings of the study explained in the previous chapter will be discussed as described in Figure 4.1. Firstly, the effect of persuasive messages on the ratings of the songs from new artists is explored. Secondly, the relation between different aspects of personality and receptiveness of persuasive messages is examined. Finally, the rating of persuasive messages by the users with the effectiveness of persuasive messages is compared.

4.1 The effect of persuasive messages on user ratings of new artists

This section begins by investigating the effect of persuasive messages on ratings of songs from new artists. Next, it explores whether explicitly mentioning that the artist is a new artist in the message changes the effectiveness of the persuasive message. Then, I compare the ten persuasive messages presented in Table 3.1 in previous chapter based on the ratings given by the participants to the playlists they saw and conclude by investigating the relationship between ratings of popular songs, ratings of songs from new artists and overall rating of the playlist.

To investigate the effect of persuasive messages on ratings of songs from new artists, the ratings received by playlist 3 are compared with the ratings received by the other playlists. As mentioned in the previous section, playlist 3 only includes songs from new artists, some with persuasive messages, some without. Figure 4.2 exhibits the average ratings of all the playlists. As the study did not explicitly mention that this playlist does not have any songs from famous artists, it can be assumed that the participants consider this playlist format the same as the others by induction. A non-parametric two-sample Wilcoxon signed-rank test is utilized because our ordinal data does not follow a normal distribution [85].

Wilcoxon signed-rank test is a non-parametric hypothesis testing method for checking whether two sample groups have been sourced from the same distribution by comparing the groups' median. This method is an alternative to the two-sample t-test hypothesis testing method for the data that is not normally distributed. For testing the normality, two methods are utilized: a quantile-quantile plot, which is a visual method comparing data distribution to the normal distribution by plotting their quantiles against each other [86]. This method showed that the data does not fit on the line. Secondly, applying Shapiro-Wilk test, which is suitable for ordinal data as the ratings of the playlists are ordinal and fits small size datasets [78]. Shapiro-Wilk test imposes a normal curve on the observations and computes the overlap as similarity percentage. Then, it calculates the probability of finding the before-mentioned similarity percentage under the exact

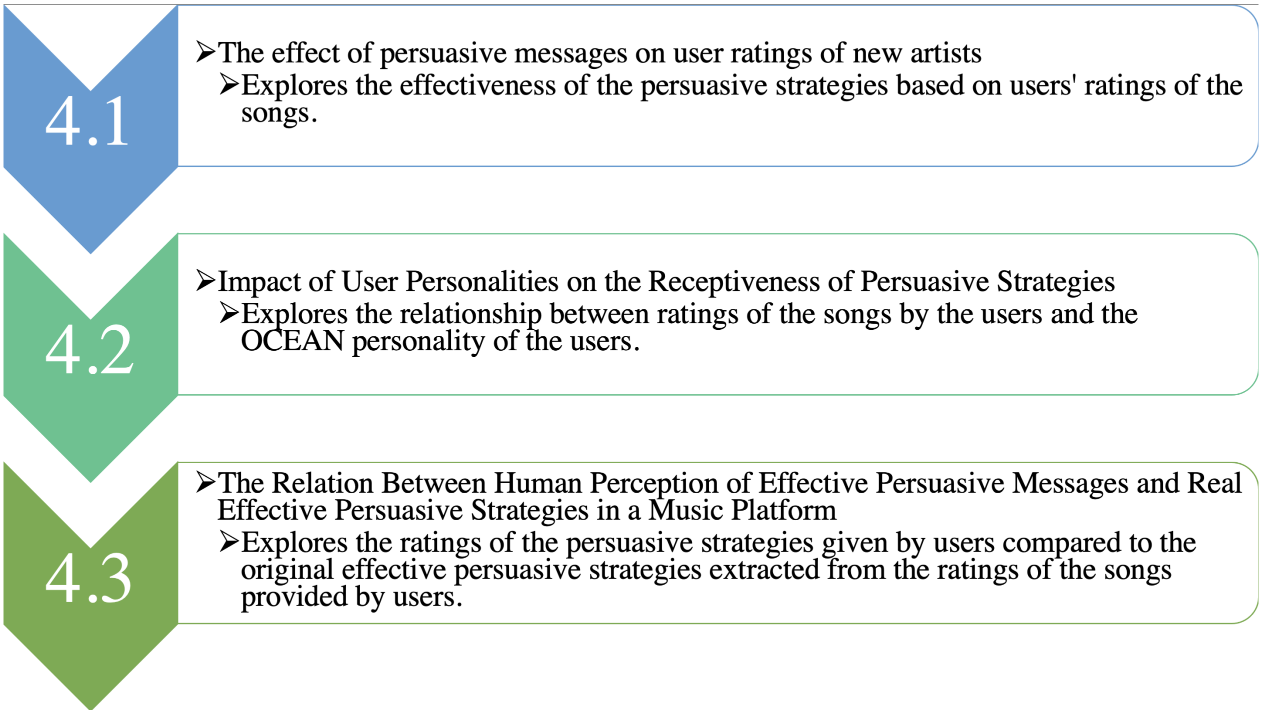


Figure 4.1: Organization of the Result Chapter

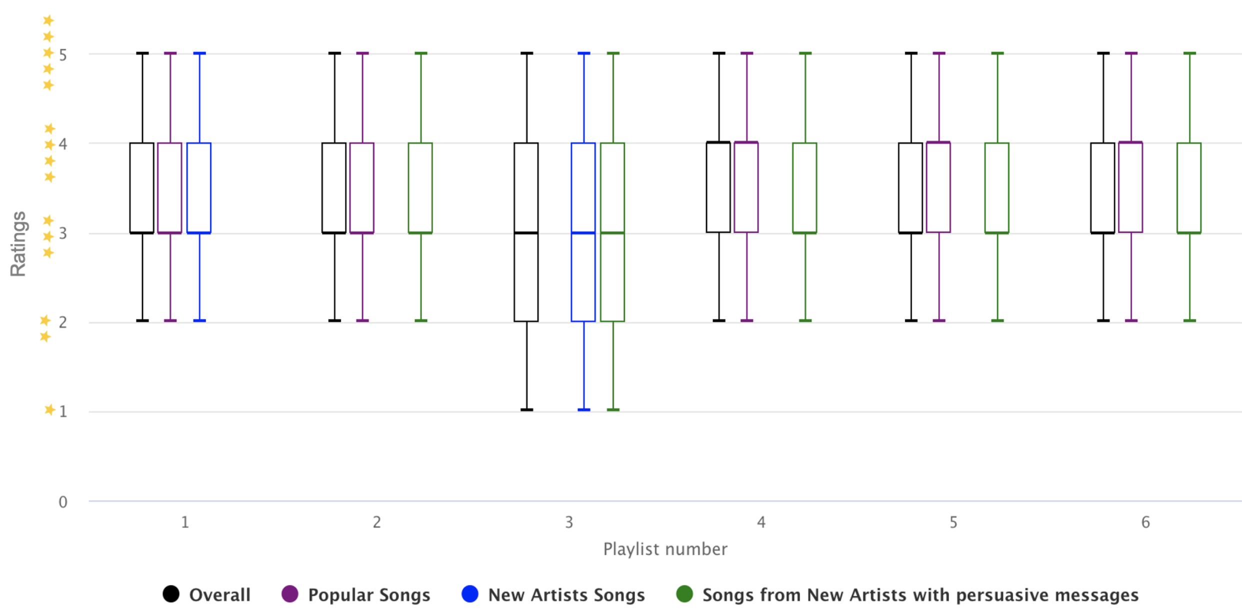


Figure 4.2: Ratings across Different Playlists

normal distribution assumption. This probability in the ratings was close to zero; therefore, our data does not follow a normal distribution ($\mathcal{P}$=6.15e−10).

Additionally, the data must meet the following three assumptions to be appropriate for using Wilcoxon signed-rank test. Firstly, the Wilcoxon sign test requires the dependent variable to be at least an ordinal scale in both groups for comparing the values. I compared the ratings of the songs from new artists with persuasive messages with songs from new artists without persuasive messages, which were both given on the same Likert scale from 1 to 5. Secondly, each case must be independent and drawn randomly. This assumption is also valid because the system users are all independent, experiencing the system individually. Thirdly, the independent variable should consist of two matched pairs, meaning the same subject should be present in both groups so that the paired observations are related. As the participants are rating all criteria in all playlists, the same user is present in the ratings of songs from new artists with/without the persuasive messages [85].

The results indicated that in playlist 3 (which contains only new songs), the songs without persuasive messages have lower ratings than the corresponding ratings in the other playlists for the popular songs($\mathcal{P}$=3.14e−6). The songs without persuasive message in the other lists were from popular artists. So when rating the songs without persuasive message the participants may have assumed that they are all by popular artists, yet these songs in playlist 3 were not, they were songs of new artists. The participants rated them lower. This is not very surprising, since they are unfamiliar to the participants. However, more interestingly, these songs from new artists have lower ratings compared to the songs from new artists with persuasive messages in other playlists($\mathcal{P}$=5.65e−11). Therefore, the persuasive messages are effective in rating the songs from new artists higher. Moreover, the overall rating of this playlist(given by users) is significantly lower than the overall ratings of the other playlists ($\mathcal{P}$=5.49e−13). This difference is also noticeable between playlist 3 and other playlists in Figure 4.2. Interestingly, in playlist 3 the songs with persuasive messagess have significantly lower ratings compared to songs with persuasive messages in other playlists ($\mathcal{P} = 0.001$). When the users realize that the quality of the playlist does not meet their expectations, their experience deteriorates and promoting songs from new artists does not drive better ratings of songs from new artists. Therefore, we conclude that a certain level of user satisfaction(by including popular artists or familiar songs) needs to be maintained to promote songs from new artists.

4.1.1 The effect of mentioning new artists on user ratings of new artists

We compare the ratings of songs from new artists in playlists that utilize mentioning new artists (playlists 2 and 5) and the playlists that do not, excluding playlist 3 that does not have the same condition as other playlists because it only includes songs from new artists. A non-parametric two-sample Wilcoxon signed-rank test revealed that mentioning the new artists leads to higher ratings of the songs from the new artists ($\mathcal{P} = 0.05$); we used this test because our data is ordinal and does not follow a normal distribution. This $\mathcal{P}$ is plausible for our sample size, considering that the controlled persuasive messages containing with/without the persuasive messages were repeated four times in the study for 205 participants. Consequently, we recommend mentioning new artists in the explanations to have a more persuasive recommendation.

4.1.2 Comparison between different persuasive messages effectiveness

For detecting the most effective messages, we computed for each user the average rating the user gave to songs of new artists over the 6 playlists. Then we selected those playlists where the user's rating of new artists' songs exceeded their own average rating. The persuasive messages used in such playlists are considered the most effective persuasive messages for the user. At last, we aggregated the repetition of the effective persuasive messages for all of the participants, referenced in Figure 4.3 as count. The investigations indicated that persuasive messages vary by ratings of songs from new artists. To check for differences between the 10 persuasive messages groups, firstly, the Analysis of variance (ANOVA) test is applied, a test that checks whether the means of two or more groups are significantly different from each other [75]. However, the most effective persuasive messages data does not comply with the ANOVA assumption of homoscedasticity. Homoscedasticity means that the variance of the residual, or error term, in a regression model is constant and follows a normal distribution. For testing the residual variance, the Shapiro-Wilk test was applied that indicated that residuals do not follow a normal distribution ($\mathcal{P}$=2.1e−16) [78].

Consequently, I applied Kruskal-Wallis one-way analysis of variance, which is an alternative to one-way ANOVA[44]. This method is a rank-based nonparametric test appropriate for comparing ten groups of different persuasive messages(based on the strategies listed in Table 3.1) on ordinal ratings as dependent variables. This method checks whether these ratings are all from the same distribution by comparing medians of the groups. The results showed that not all persuasive messages are equally effective ($\mathcal{P}$=2.2e−16).

As for comparing methods with each other, songs with persuasive messages based on *Authority, Social influence with mentioning new artist, Social influence without mentioning new artist, Scarcity with mentioning new artists, Empathy, and Purpose* have higher ratings compared to the rest of the methods using Wilcoxon signed-rank paired sample test ($\mathcal{P} = 0.001$) [85]. Analyzing persuasive messages used with songs that a user has rated higher than their individual average also shows this difference in Figure 4.3.

Mentioning that the song is from a new artist is obviously important, as two of the three most effective strategies mention *new artist*. This can be explained with an implicit effect of the Commitment strategy, as the users have seen in the consent form the purpose of the study to investigate how to better promote new artists and overcome the unfairness of the superstar economy in the music industry. The interesting result worth mentioning is that the explicit application of the strategy in the message " *This song is included because you agreed to have fair recommendations*" was not as effective; perhaps it was considered too blunt a reminder. Further work is needed to uncover the reasons for this discrepancy.

Authority is a powerful persuasive strategy, as most of the users are not music experts and trust the knowledgeable and credible experts' opinions for evaluating songs from new artists. This outcome is aligned with Orji et al. [60] and Oyibo et al.'s [64] studies on employing persuasive strategies for behaviour change,

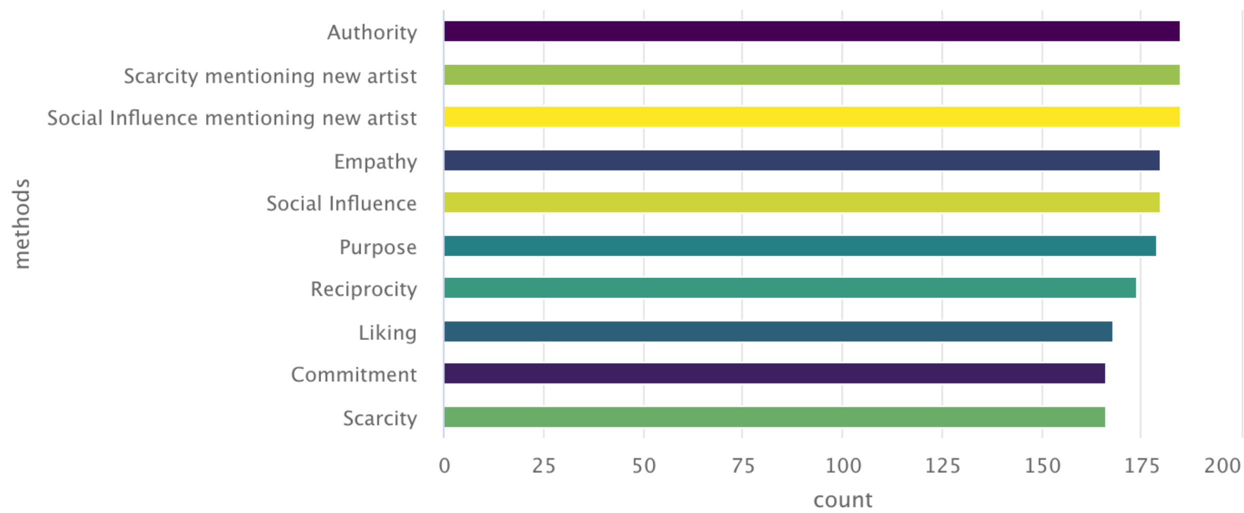


Figure 4.3: Comparing methods used in playlists that a user has rated higher than their individual average rating of new songs.

indicating *Authority* as an effective persuasive method. However, these studies found that *Commitment* and *Reciprocity* were also among the top effective strategies for building healthy habits. In contrast, our result indicates that *Social Influence* is an equally effective persuasive strategy which suggests that participants consider other users' ratings in their decision-making process. This difference is explainable as our study aims at making the user trust the recommendations instead of changing behaviour. On the other hand, our results comply with [30], which found *Authority* and *Social Influence* as the most effective persuasive methods for explaining the recommendations.

4.1.3 The relation between ratings of new songs, popular ratings and overall rating

In this section, the effect of ratings of popular songs and songs from new artists on the overall ratings of the playlists is explored. The correlation between these ratings is summarized in Table 4.1 using Kendall rank correlation. Kendall rank correlation is a non-parametric test that measures the ordinal association between two quantities by comparing the similarity between the order of the ranks in data for the quantities [41]. For this problem, the ranking is based on the rating of the playlists, rating of the songs from new artists and rating of the popular songs. I applied this method as the ratings are ordinal and do not follow a normal distribution. For testing the normality for each of the three rating criteria, the Shapiro-Wilk test was applied and rejected the normal distribution hypothesis ($\mathcal{P}$=2.2e$-$16, $\mathcal{P}$=2.2e$-$16, $\mathcal{P}$=2.2e$-$16).

Additionally, this method is better than other methods for a small sample size with many tied ranks [41]. When observations have a similar rank, for instance, ordinal ratings of the playlists for ratings of popular songs and the overall rating of the playlist, the Kendall correlation will be high between the two variables. When observations have a different rank, the Kendall correlation between the two variables will be small.

Table 4.1: Correlation between popular rating, ratings of songs from new artists and overall rating.

Attribute	Attribute	tau	p-value
Overall Rating	Popular Rating	0.67	2.2e−16
Overall Rating	Rating of songs from new artists	0.63	2.2e−16
Popular Rating	Rating of songs from new artists	0.35	2.2e−16

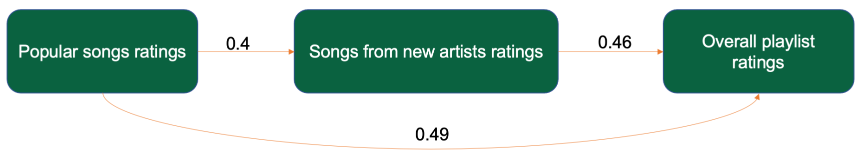


Figure 4.4: Standardized path coefficients and significance of the model.

Our results exhibit a positive correlation between overall ratings with popular songs and songs from new artists. Moreover, there is a positive correlation between ratings of popular songs and songs from new artists.

Comparing the importance of popular songs and songs from new artists on the overall rating of the playlist, I applied a structural equation model(SEM) for predicting overall rating [34]. SEM is a quantitive research technique that is utilized for showing causal relationships between the variables, and it is widely used in social and behavioural sciences. It explores linear causal relationships between variables while adjusting measurement error, similar to regression analysis but more robust. SEM incorporates three components:

- Model, which is a design of a theoretical phenomenon. This model shows the structure of relations between different variables.
- The structure shows the relationship between different variables, error terms and causal relationships incorporating multiple equations.
- The equations are extracted from the model and its structural features and then predicted with statistical methods.

The path coefficient is calculated using path analysis techniques to evaluate the strength of the link between variables [24]. The individual path coefficients and their corresponding level of significance obtained from the SEM models are shown in Figure 4.4. The model identifies a more statistically significant coefficient for the popular ratings, meaning that the quality of popular songs is more important in the user's overall experience, with coefficients of 0.45 for songs from new artists and 0.49 for popular songs.

Table 4.2: Summary of Ratings of songs from new artists based on Gender.

Gender	Count	Mean	STD
Female	135	3.36	0.996
Male	65	3.16	0.957
Prefer not to answer	5	3.7	1.12

4.2 Impact of User Demographics and Personalities on their Receptiveness of Persuasive Strategies

This section explores the impact of different demographic features on the ratings of songs from new artists. This information provides a better understanding of the participants' behaviour, leading to personalized guidelines for designing persuasive fair music recommender systems. Moreover, this section researches the most effective persuasive methods for various participants' demographic characteristics and OCEAN personalities based on the rating they gave to the songs from new artists. This analysis explores patterns in the data, since they can be useful for future studies. Since the main reason for non-conclusive results regarding the demographic differences seems to be the unbalanced representation of these differences among the participants in this study, the general recommendation for future research is to have balanced and larger user groups with respect to the target demographics under investigation. Prior literature has shown that tailoring persuasive messages to user personalities will increase the impact of persuasive messages [33]. Therefore, these measures can be applied in designing more effective multi-stakeholder recommender systems.

4.2.1 Gender

To assess the difference between three gender groups, male, female, and prefer not to answer, the ANOVA assumption of homogeneity of variance is checked using Levene's Test [46]. The summary of ratings of songs from new artists based on genders is summarized in Table 4.2. ANOVA assumes that the variances of different populations are equal, and Leven's test validates this assumption. The significant p-value of this test shows that the differences between sample variances of different populations are unlikely to be caused by random sampling from the same populations; therefore, there is a distinction between populations. Levene's test result indicated that variance between gender groups is not homogenous. Subsequently, Kruskal-Wallis one-way analysis of variance is employed for checking whether different genders exhibit different ratings for songs from new artists[44]. The result shows a significant difference between different genders in ratings of songs from new artists ($\mathcal{P}$=0.0004).

For further investigation of the difference, the ratings of songs from new artists for females and males are compared using Wilcoxon signed-rank test. This test is utilized because our ordinal data does not follow a normal distribution [85]. The outcome showed significant evidence that women tend to rate songs from new

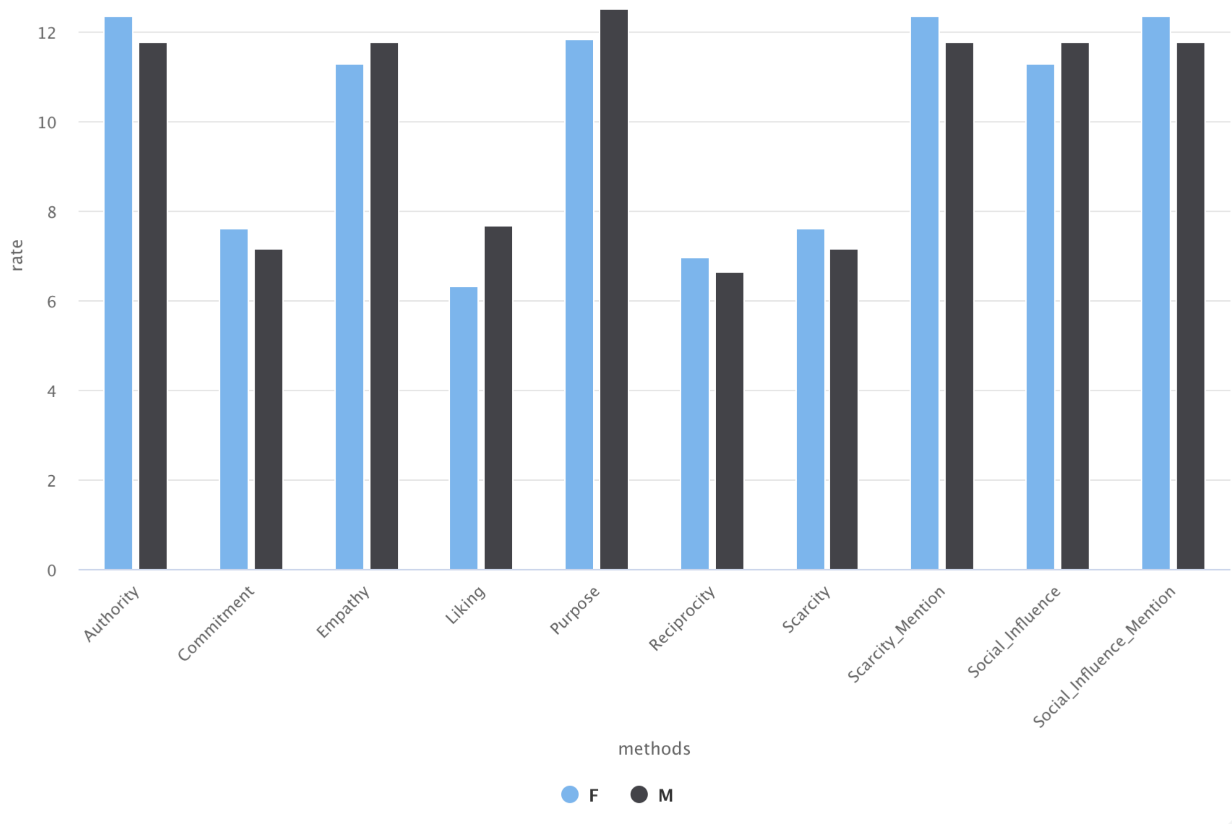


Figure 4.5: Most Effective Persuasive Methods for Genders.

artists higher than men ($\mathcal{P}$=0.0007).

Personalizing Persuasive Messages for Promoting New Artists Based on Gender

Figure 4.5 shows the most effective persuasive methods for each gender in each gender category as the percentage of users that the persuasive strategy was effective for, referenced as rate in Figure 4.5 and other figures in this section. As it was explored in the prior section, the most effective persuasive messages for all of the users were *Authority, Social Influence with mentioning new artist, and Scarcity with mentioning new artists*. The most effective methods for men were *Social Influence*, *Empathy*, *Purspose* and *Liking* leading to significantly higher ratings of songs from new artists compared to the rest of the methods ($\mathcal{P}$=0.005). The most effective methods for women were distinctive from men *Social Influence Mention*, *Scarcity*, *Scarcity Mention*, *Reciprocity*, *Commitment*, and *Authority* leading to significantly higher ratings of songs from new artists compared to the rest of the methods ($\mathcal{P}$=2.2e−16).

Table 4.3: Summary of Ratings of songs from new artists based on Age.

Age	Count	Mean	STD
<17	2	2.92	1.31
18-24	113	3.32	0.997
25-34	66	3.33	0.983
35-44	15	3.17	0.927
45-54	5	3.73	0.868
>55	4	2.83	1.05

4.2.2 Age

The differences between different age groups are compared using two methods: firstly, investigating whether a particular age group has a significantly different rating of songs from new artists compared to other age groups. Secondly, examining the existence of a linear relationship between age groups and ratings of the songs from new artists. The summary of ratings of songs from new artists based on age range is summarized in Table 4.3.

I follow the same procedure as described in the previous chapter to find the distinction between varying age groups. As the age range is an ordinal attribute, the Shapiro-Wilk test is appropriate for checking the normality assumption concerning ANOVA [75, 78]. Shapiro-Wilk test result confirmed that data does not follow a normal distribution ($\mathcal{P}$=2.2e−16); hence, Kruskal-Wallis analysis of variance test suits for comparing different age groups. The null hypthesis is checking whether the ratings of the songs from new artists from different age groups all are from the same distribution. Unfortunately, the p-value for the Kruskal-Wallis test was not significant enough to refute the null hypothesis. Therefore, it can not be verified that a notable difference exists in the ratings for different age groups.

To explore more, the relation between the age groups and ratings of the songs from new artists is investigated, checking whether there is a linear relationship between the rating and the age of the participants. The correlation between age groups and the ratings of songs from new artists is explored using the Kendall rank correlation [41]. I applied this method as the ratings are ordinal and do not follow a normal distribution. However, the correlation p-value was not significant to indicate any linear relationship between age and ratings of songs from new artists.

Personalizing Persuasive Messages for Promoting New Artists Based on Age

Figure 4.6 shows the most effective persuasive methods for each age range as the percentage of users in each age category that were most influenced by the persuasive methods. The most effective persuasive methods for 18-24, 25-34, and 45-54, which comprise 87% of the participants, were again *Authority, Social influence with mentioning new artist, and Scarcity with mentioning new artists*. However, considering the 35-44 age range,

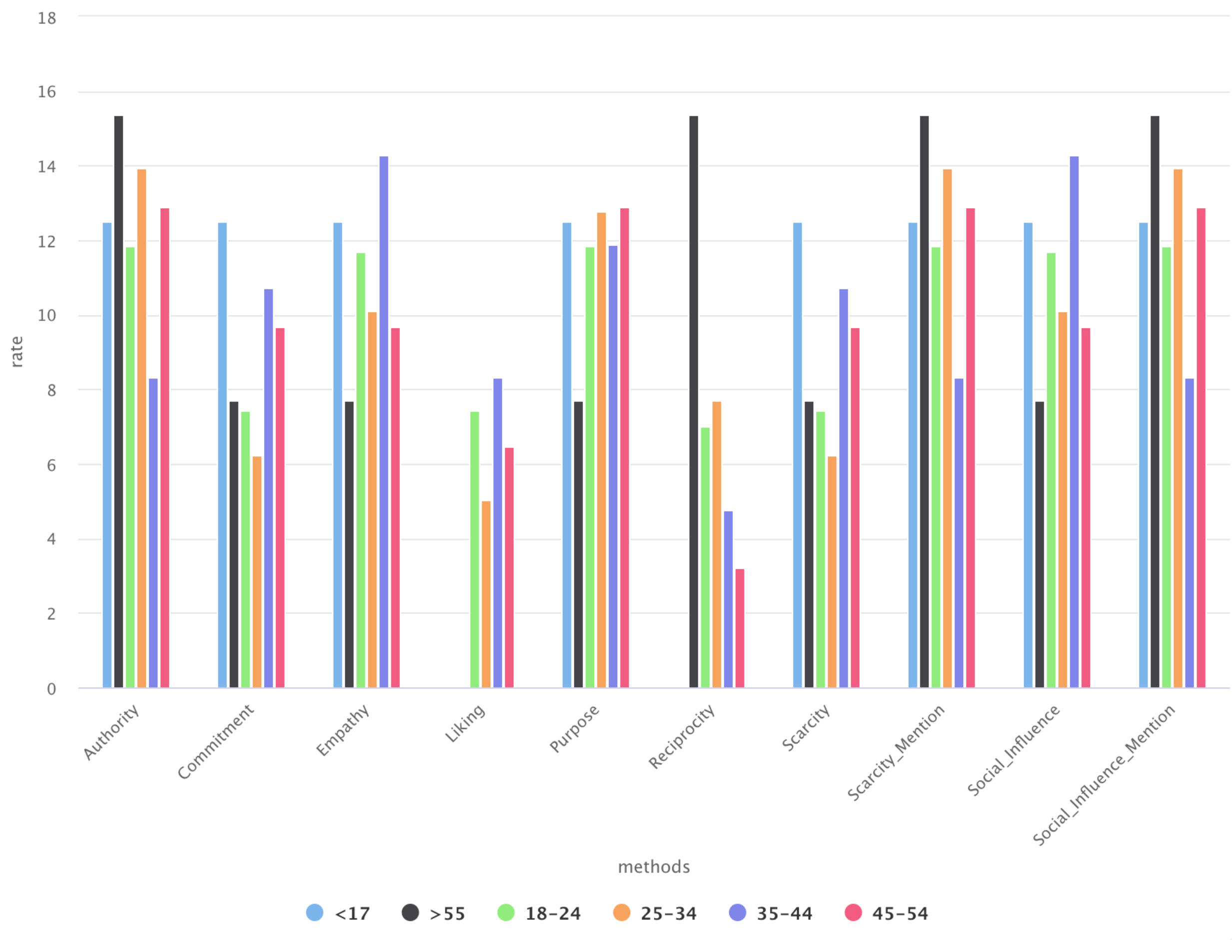


Figure 4.6: Most Effective Persuasive Methods for Age groups.

the top three most effective persuasive messages for this group were *Social Influence, Empathy and Purpose.* The +55 age range had the most effective persuasive messages same as the most effective methods for all users of the system *Authority, Social influence with mentioning new artist, and Scarcity with mentioning new artists*. However, this group were influenced by *Reciprocity* as much as much as the mentioned strategies.

4.2.3 Birth Continent

The differences between birth continents and the ratings of the songs from new artists match the same steps as analyzing the gender attribute. The summary of ratings based on birth continent is summarized in Table 4.4. Levene test did not dispense a significant p-value regarding the difference between variance of different birth continents; thus, the data is homogenous. However, the Shapiro-Wilk test showed that the data did not follow a normal distribution. Comparing group means using the Kruskal-Wallis test did not yield significant differences in ratings between different birth continents.

Table 4.4: Summary of Ratings of songs from new artists based on Birth Continent.

Gender	Count	Mean	STD
Africa	5	3.6	0.968
America	123	3.3	0.968
Asia	61	3.33	1.01
Australia	1	3.83	1.17
Europe	11	3.21	0.969

Personalizing Persuasive Messages for Promoting New Artists Based on Birth Continent

Figure 4.7 shows the most effective persuasive methods for users based on their birth continent as the percentage of users in each continent that were influenced by the persuasive methods. The figure only shows the data for the America and Asia continents as 90% of the participants were born in these continents. The pattern for each of the continents was aligned with the system's overall most effective persuasive messages, except for Africa that presented *Reciprocity* as an effective method. Table 4.5 summarizes the effectiveness of the persuasive strategies based on the continent of birth.

Asians show the largest differences in their perceived influence of the strategies: they have so low impact of *Reciprocity, Scarcity, Liking and Commitment*, even *Social Influence* and *Empathy* are pretty low in comparison to the 4 main influence strategies that are common for all groups. Africans seem to be motivated nearly equally by all strategies without *Liking, Purpose* and *Scarcity.* Australians too, but they are not motivated by *Liking* at all. Americans, which are the largest group, are motivated by *Purpose* and *Empathy* nearly the same as *Scarcity-Mention, Social-Influence-Mention, Social Influence* and *Authority.*

4.2.4 Daily Listening Habits

The music listening habit is divided into 3 categories of less than 1 hour, between 1 to 3 hours, more than 3 hours, in which the user answered in the questionnaire at the beginning of the study. The analysis of daily listening habits did not exhibit any difference between the ratings of songs from new artists among users who listen to music less than 1 hour, 1 to 3 hours, and more than 3 hours daily. The summary of ratings of songs from new artists based on daily music listening habit is summarized in Table 4.6.

Personalizing Persuasive Messages for Promoting New Artists Based on Daily Music Listening Habit

Figure 4.8 shows the most effective persuasive methods based on users' daily music listening habits. There are no significant differences between different music listening habits groups regarding the most effective messages, and the most effective persuasive strategies remained *Authority, Purpose, Social Influence with mentioning new artist, and Scarcity with mentioning new artists* methods. Additionally, *Liking* and *Reciprocity* have the

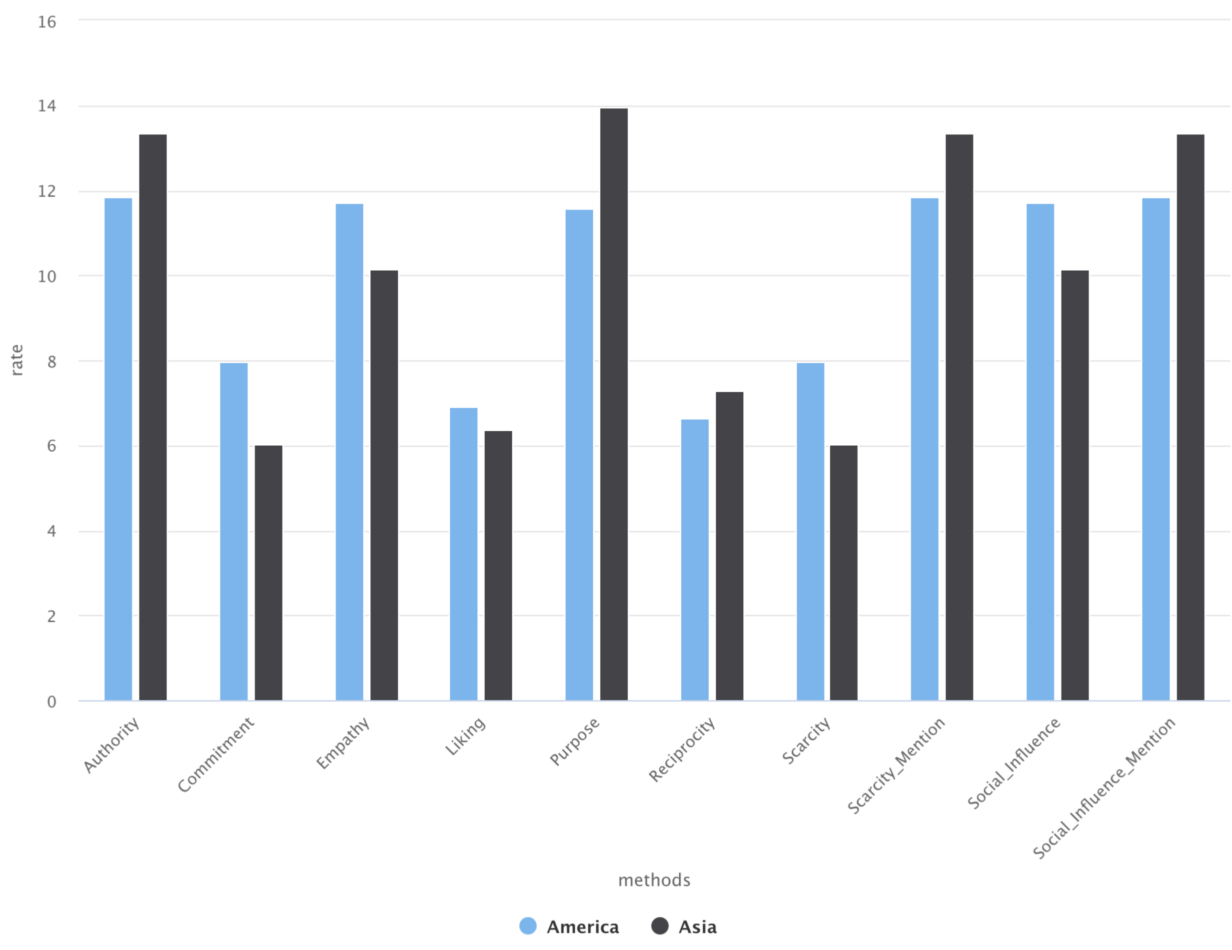


Figure 4.7: Most Effective Persuasive Methods for Birth Continents.

Table 4.5: Summary of the strength of persuasive methods based on Birth Continent.

Birth Continent	Strong	Medium	Weak
America	Authority, Empathy, Purpose, Scarcity Mention, Social Influence, Social Influence Mention	Commitment, Scarcity	Liking, Reciprocity
Asia	Authority, Purpose, Scarcity Mention, Social Influence Mention	Empathy, Social Influence	Reciprocity, Scarcity, Liking, Commitment
Africa	Authority, Empathy, Reciprocity, Scarcity Mention, Social Influence, Social Influence Mention	Commitment, Scarcity	Liking, Purpose
Europe	Authority, Empathy, Purpose, Scarcity Mention, Social Influence, Social Influence Mention	Commitment, Liking, Reciprocity, Scarcity	-
Australia	Authority, Commitment, Empathy, Purpose, Reciprocity, Scarcity, Scarcity Mention, Social Influence, Social Influence Mention	-	Liking

Table 4.6: Summary of Ratings of songs from new artists based on Music Listening Habit.

Listen to Music (hours)	Count	Mean	STD
<1	50	3.24	0.93
1-3	105	3.31	1.02
>3	50	3.31	1.00

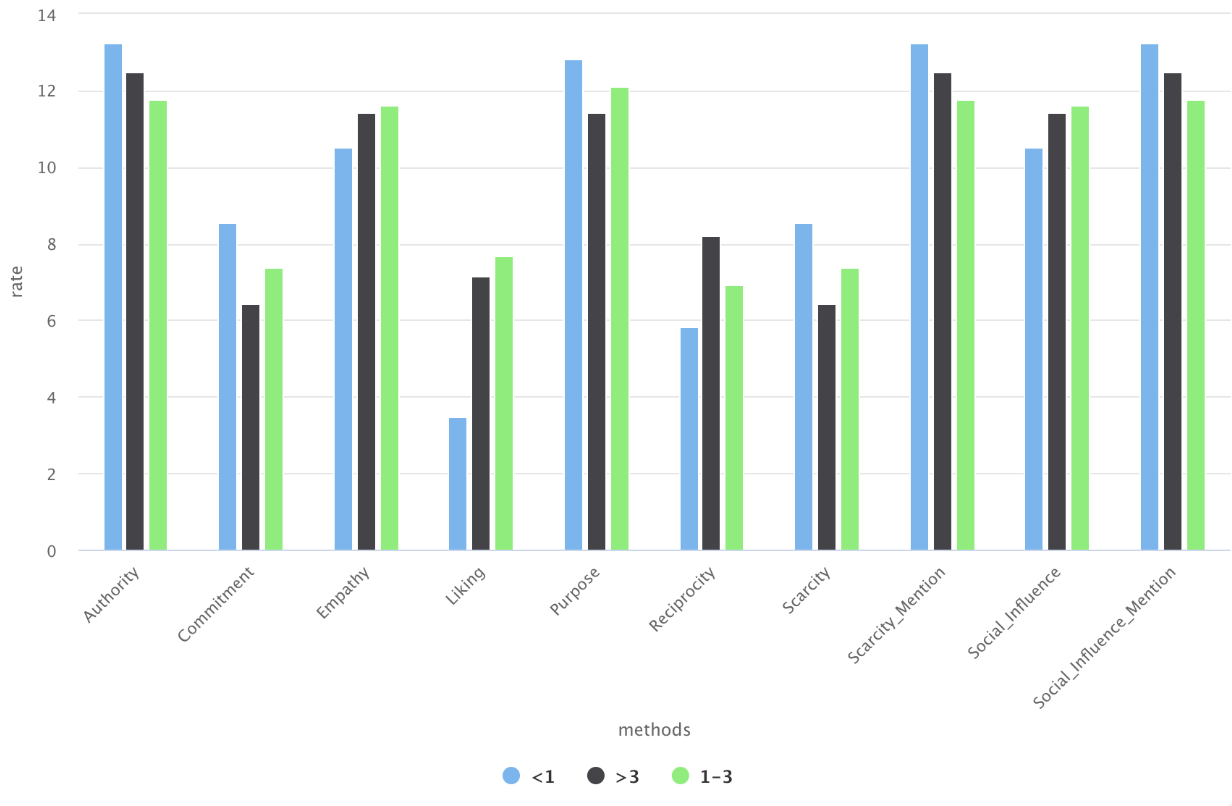


Figure 4.8: Most Effective Persuasive Methods for Music Listening habits.

least influence on persuading users.

4.2.5 Favourite Genre

The summary of ratings of songs from new artists based on the favourite genre is summarized in Table 4.7. Comparing participants' favourite genres and ratings of the songs from new artists using the Kruskal-Wallis test revealed that different genres had different variances. The results show that users with different favorite music genres rated songs of new artists differently. I used the Kruskal-Wallis test because the Levene test of variance homogeneity showed that different groups did not have the same variance.

Specifically, using Wilcoxon signed-rank test [85] I found that songs of new artists in Indie/Alternative genre received significantly higher ratings than those in any other genre ($\mathcal{P}$=0.007). This result is not surprising since users who like the alternative genre, which is a genre that provides a new alternative way to the rock genre, are willing to explore new experiences. Consequently, new artists in this genre have a higher chance of being heard compared to other genres.

Personalizing Persuasive Messages for Promoting New Artists Based on Favourite Genre

Figure 4.9 shows the most effective persuasive methods for users' favourite genre as the percentage of users that were influenced by the persuasive methods in each genre. Table 4.8 summarizes the effectiveness of the

Table 4.7: Summary of Ratings of songs from new artists based on favourite genre.

Gender	Count	Mean	STD
Country	32	3.28	1.05
Dance	38	3.18	1.10
Hip-Hop/Rap	34	3.13	0.999
Indie/Alternative	97	3.40	0.918
Metal	20	3.02	0.983
Pop	109	3.27	0.977
R&B	24	3.61	0.983
Rock	56	3.39	0.986

persuasive strategies for each genre.

4.2.6 Importance of Fairness

Kendall's Correlation test did not show significant linear or semi-linear relationship between the declared importance of fairness by the user at the start of the study and their ratings of new artists songs ($\mathcal{P}$=0.64). Thus, the declared importance of fairness by the users is not related to ratings they gave to songs from new aritsts. Further investigation also revealed that users who assigned higher importance to promote songs from new artists did not rate songs from new artists higher than users who assigned lower importance scores.

4.2.7 Personality Assessment

The relationship between different OCEAN personality attributes and ratings of the songs from new artists is investigated via the correlation test. The summary of the correlation coefficients, along with their p-values, are presented in Table 4.9. The results indicated that all personalities except conscientiousness play a role in the ratings of the songs from new artists. Open-minded people are willing to gain new experiences, giving new artists a chance to be listened to. Additionally, agreeable users tend to conform with the objective of the recommender system, which is promoting songs from new artists in a persuasive approach, hence giving higher ratings of the songs from new artists compared to users with hostile personalities.

Personalizing Persuasive Messages for Promoting New Artists Based on OCEAN Personality

Figure 4.10 shows the most effective persuasive strategies for each OCEAN personality attribute showing the percentage of users that have chosen each method as the most effective method. Each personality attribute is assessed with a score on a scale from 0 to 100. As the averages of the attribute scores were 50, the attribute scores less than 50 were calculated as Low. If the attribute scores were more than 50 and less than 75, they were considered medium, and personalities above 75 were grouped as high. The most effective methods for

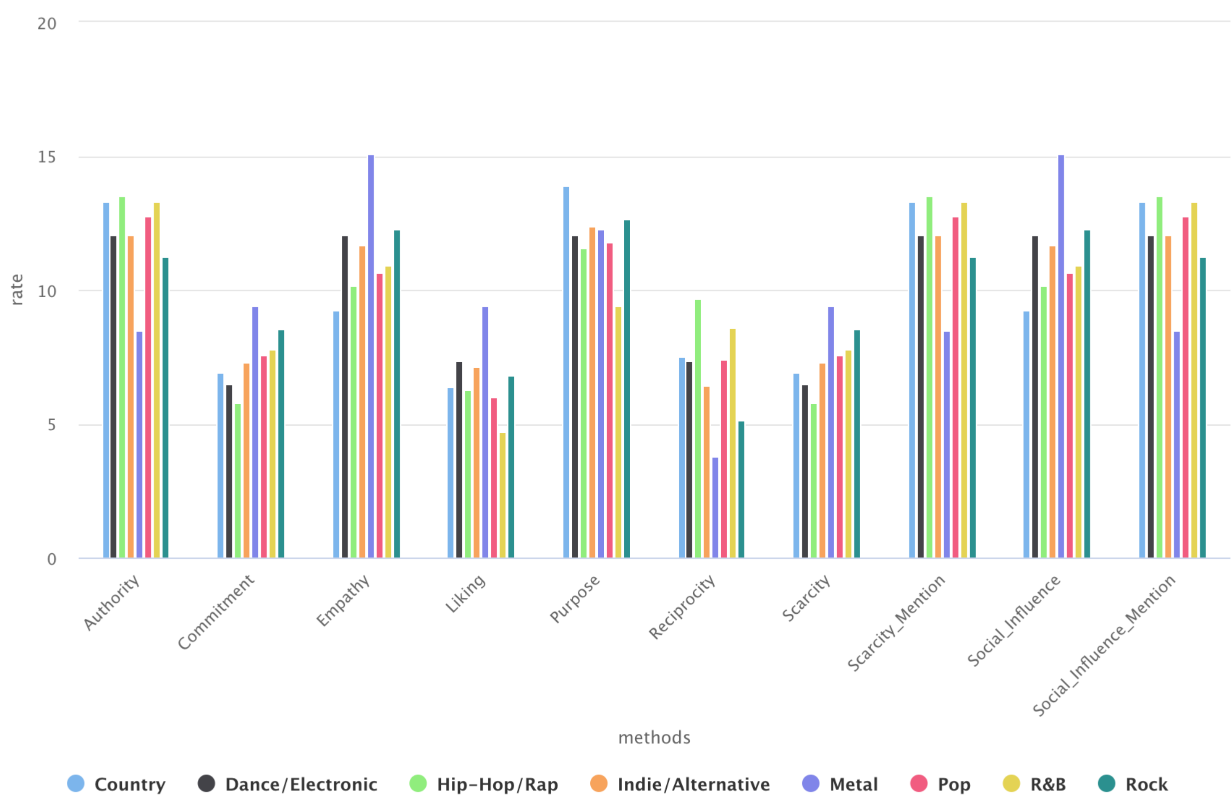


Figure 4.9: Most Effective Persuasive Methods for Favourite genres.

Table 4.8: Summary of the strength of persuasive methods based on Genre.

Genre	Strong	Medium	Weak
Country	Authority, Purpose, Scarcity Mention, Social Influence Mention	Empathy, Social Influence	Commitment, Liking, Reciprocity, Scarcity
Dance/Electornic	Authority, Empathy, Purpose, Scarcity Mention, Social Influence, Social Influence Mention	-	Commitment, Liking, Reciprocity, Scarcity
Hip-Hop/Rap	Authority, Scarcity Mention, Social Influence Mention	Empathy, Purpose, Reciprocity, Social Influence	Commitment, Liking, Scarcity
Indie/Alternative	Authority, Empathy, Purpose, Scarcity Mention, Social Influence, Social Influence Mention	-	Commitment, Liking, Reciprocity, Scarcity
Metal	Empathy, Social Influence	Commitment, Liking, Purpose, Scarcity, Scarcity Mention, Social Influence Mention	Reciprocity
Pop	Authority, Purpose, Scarcity Mention, Social Influence Mention	Empathy, Social Influence	Commitment, Liking, Reciprocity, Scarcity
R&B	Authority, Scarcity Mention, Social Influence Mention	Commitment, Empathy, Purpose, Reciprocity, Scarcity, Social Influence	Liking
Rock	Authority, Empathy, Purpose, Scarcity Mention, Social Influence, Social Influence Mention	Commitment, Scarcity	Liking, Reciprocity

Table 4.9: Correlation between OCEAN Personality Traits and Ratings of songs from new artists.

Personality Trait	Coefficient	p-value
Openness	0.12	$\mathcal{P}$=2.79e−5
Conscientiousness	0.04	$\mathcal{P}$=0.14
Extroversion	0.08	$\mathcal{P}$=0.005
Agreeableness	0.1	$\mathcal{P}$=4.09e−4
Neuroticism	0.08	$\mathcal{P}$=0.006

the users with low and medium openness score were *Authority, Scarcity with Mentioning New Artist, and Social Influence with Mentioning New Artist*. On the other hand, the most effective methods for users with a high openness score were *Empathy, Social Influence, and Purpose*.

Regarding conscientious, each of the three groups behaved differently. The most valuable methods for low conscientiousness score were *Empathy, and Social Influence*. For medium conscientiousness score, the most influential method was *Purpose*. The most powerful methods for the high conscientiousness scores were *Authority, Scarcity with Mentioning New Artist, and Social Influence with Mentioning New Artist*.

Authority, Scarcity with Mentioning New Artist, Social Influence with Mentioning New Artist, and Purpose were the most effective methods for users with low or medium conscientious score. The most effective methods with a high conscientious score were *Empathy, Social Influence, Scarcity, and Commitment*.

Concerning Agreeableness, the most effective method for users with low agreeableness score was *Purpose* by a noticable amount. *Authority, Scarcity with Mentioning New Artist, and Social Influence with Mentioning New Artist* were the most influential methods for medium agreeableness score. The most influential methods for the high agreeableness score were *Purpose, Empathy, and Social Influence*.

Authority, Scarcity with Mentioning New Artist, Social Influence with Mentioning New Artist, and Purpose were the most effective methods for the low neuroticism scores. For the medium scores, the most practical methods were *Authority, Scarcity with Mentioning New Artist, and Social Influence with Mentioning New Artist*, The most effective methods for the high agreeableness scores were *Empathy, Purpose, and Social Influence*.

One point to note about the most effective methods was the ordering of the methods. The most effective methods for each personality were more or less the same. However, ranking based on their effectiveness, the order of methods was distinctive from each other. Figure 4.11 displays the most effective methods for each combination of OCEAN personality attributes. If an attribute is more than 50, it is counted as 1, and 0 means the attribute score is less than 50. The outcome of this figure specifies the most effective methods for each combination of personality attributes as the percentage of users that were influenced by the persuasive methods in each category. Different combinations of personalities have distinctive effective persuasive strategies. For instance, the *Liking* strategy was not an effective strategy considering all the users together. However, *Liking* is effective for several combinations of OCEAN personalities, as shown in Figure 4.11. The findings analyzed in this section could be used to design personalized persuasive strategies based on users' OCEAN personalities.

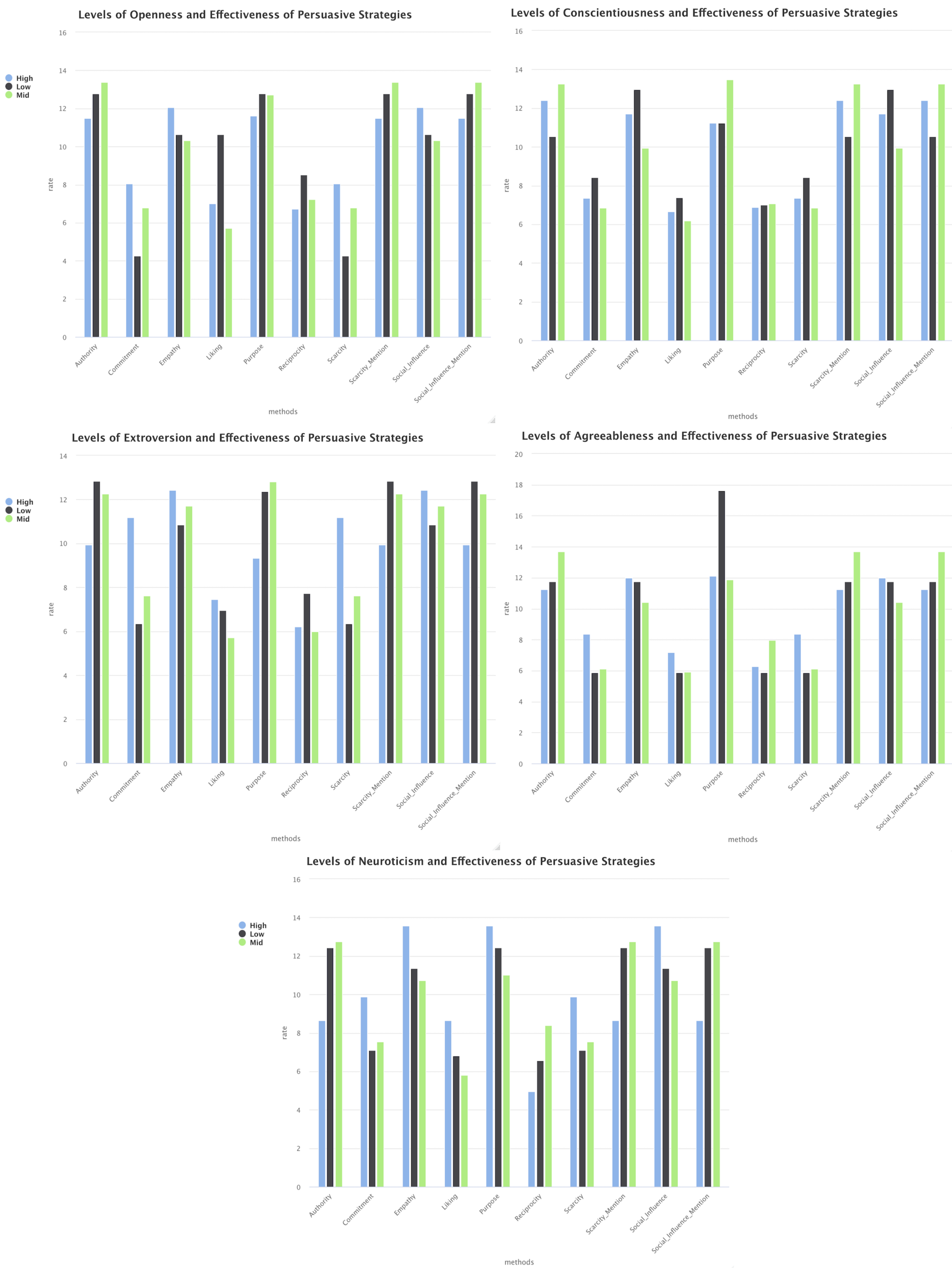


Figure 4.10: Effective Persuasive Methods for Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism Personality.

Figure 4.11: Effective Persuasive Methods for OCEAN Personalities Combinations.

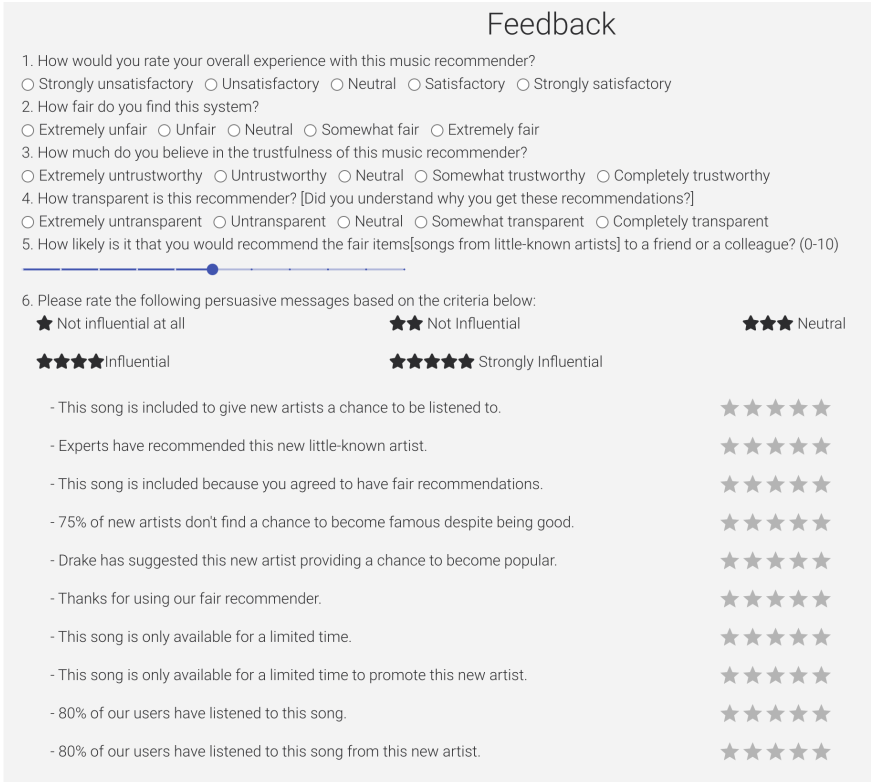


Figure 4.12: The Final Questionnaire, after rating of the playlists.

4.3 The Relation Between Human Perception of Effective Persuasive Messages and Real Effective Persuasive Messages in a Music Platform

In the study, the users were prompted to rate the effectiveness of the ten persuasive messages on a Likert scale from 1 to 5, from the least effective to the most effective in the final questionnaire, after rating all of the playlists. Figure 4.12 shows this questionnaire on the study website. This section will present the analysis of direct users' ratings of persuasive messages. Firstly, a comparison between the most effective persuasive messages based on user evaluation and the effective persuasive messages based on ratings of the playlists will be made to identify over-rated and under-rated persuasive messages. Secondly, the relationship between the most effective and the least effective methods and the participants' demographic information and personalities will be studied.

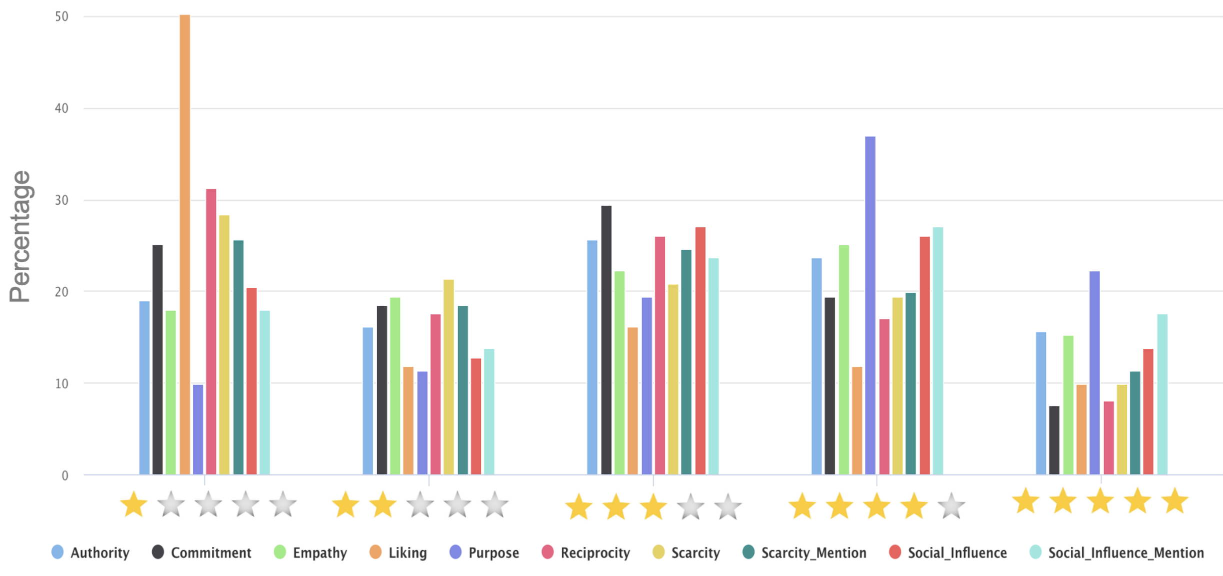


Figure 4.13: Ratings of the persuasive messages based on user ratings.

4.3.1 Investigating Overestimated and Underestimated Persuasive Strategies for Effectiveness

After rating all playlists, users were redirected to the final questionnaire to rate ten persuasive messages utilized during the study on a Likert scale from 1 to 5. Figure 4.13 displays the percentage of the users that rate a persuasive message 1-star to 5-star. Table 3.1 presents the persuasive messages used in the study. The *Liking* and *Reciprocity* persuasive strategies received the lowest ratings. Among top-rated messages, *Purpose* and *Social Influence* with mentioning new artist obtained the highest ratings.

To determine the overestimated and underestimated persuasive strategies, the participants' top-rated persuasive messages and, on the other side, the most effective persuasive messages based on participants' ratings of songs from new artists should be determined. A persuasive message is considered top-rated if the participants have rated the persuasive message higher than their individual average rating of the messages in the final questionnaire. The process for identifying the influential persuasive messages based on the user ratings of new songs in the playlists is more complicated as each persuasive strategy is applied twice throughout the 8 playlists during the study. Therefore, I define the persuasive message influence denoted by "Influence" in Equation 4.1 whether the participants have rated the songs from new artists of the playlist for which the message was applied higher than their individual average ratings of songs from new artists throughout all of the playlists (defined as User rating in Equation 4.1). Then, a persuasive message is acknowledged as influential if the summation of its influence throughout the playlists is positive as described in Equation 4.1.

$$
\begin{aligned}
\text{User Rating} &= \sum_{i=1}^{i=6} \text{Rating}_i/6 \quad \text{i: playlist number} \\
\text{Influence}_{\text{strategy}_j} &= \begin{cases} 1, & \text{Rating}_j > \text{User Rating} \\ 0, & \text{otherwise} \end{cases} \\
\text{IsInfluencial}_{\text{strategy}} &= \begin{cases} true, & \sum_j \text{Influence}_{\text{strategy}_j} > 0 \\ false, & \text{otherwise} \end{cases}
\end{aligned}
\tag{4.1}
$$

j: the number of two playlists in which the message is displayed.

Afterwards, the persuasive messages are compared in Figure 4.14 with the following labels:

- User Overestimated: The persuasive message was in the user's highest-rated persuasive messages, but it was not actually effective based on ratings of the playlists.
- User Underestimated: The persuasive message was not in the user's highest-rated persuasive messages; however, it was effective and led to high ratings of the playlists.
- User Correctly Estimated Influential Strategy: The user assigned a high rating to the persuasive strategy, and it was effective based on ratings of the playlists.
- User Correctly Estimated Uninfluential Strategy: The user assigned a low rating to the persuasive strategy, which was ineffective as it resulted in low ratings of the playlists.

The overall behaviour of the user in the evaluation of the persuasive strategies is that 38.25% of the time, users correctly estimated the effectiveness of either influential or uninfluential strategy, 33.70% of the time the users underestimate the effectiveness of the strategy, and 28.05% of the time users overestimated the effectiveness of the strategy. For evaluating the users' most dominant persuasive strategy effectiveness estimation behaviour, the highest reoccurring overestimating/underestimating/correctly estimating is considered as the users' dominant behaviour. If we only consider the users' dominant behaviour, 66% of the users' dominant behaviour is correctly estimating the influence of persuasive strategy, 27% of the users' dominant behaviour is underestimating the influence of persuasive strategy, and 8% the users' dominant behaviour is overestimating the influence of persuasive strategy.

Additionally, the users tended to underestimate the persuasive methods' actual power to convince users to listen to songs from new artists in this study. Among the ten persuasive messages, *Empathy* and *Scarcity with Mentioning new artists* were the most underestimated. 43.13% of the users underestimated the efficiency of *Scarcity with Mentioning new artists* message, and 36.49% of the users underestimated the efficiency of the *Empathy* message. The scarcity effect is a cognitive bias that attracts people to value a scarce object more than readily available objects. Based on the participants' judgment, *Scarcity* was not an effective method, but considering the outcome of the ratings, that this method turns out to be effective.

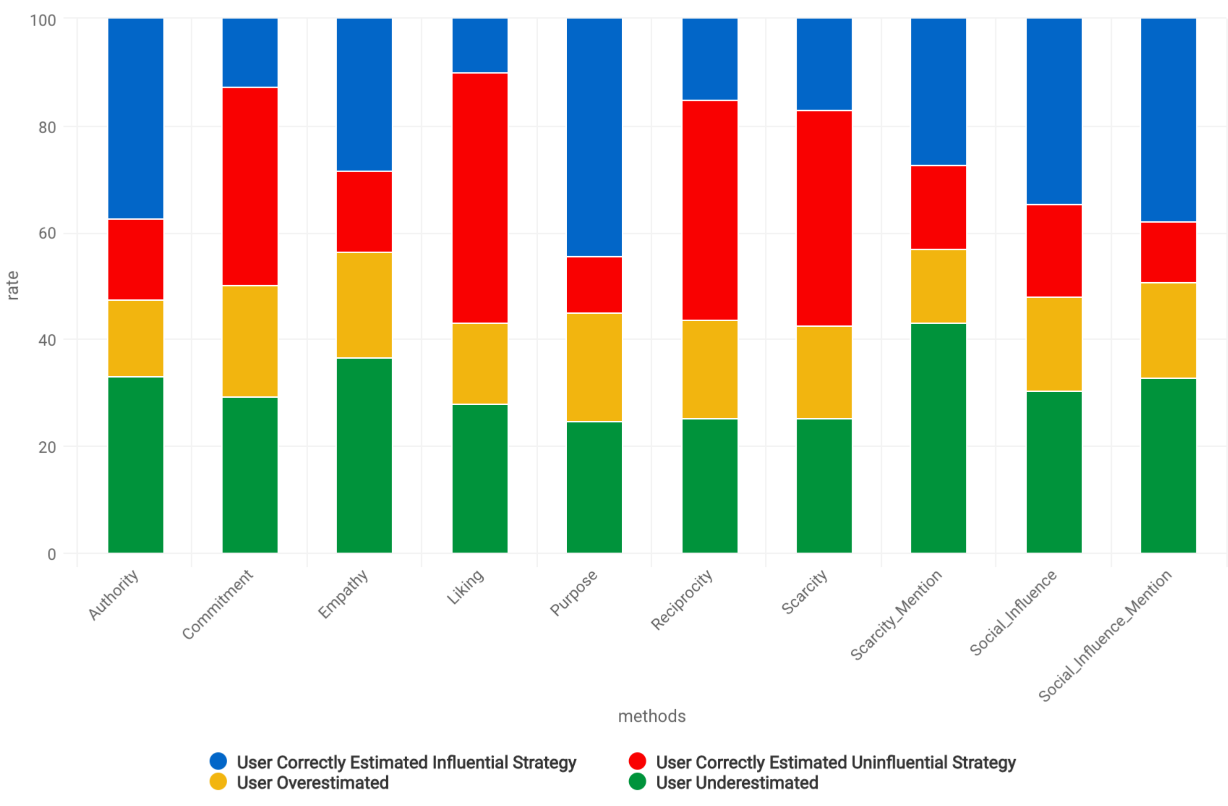


Figure 4.14: Effective strategies versus User's perception of most effective strategies.

The most overestimated methods were *Commitment*, in which 20.85% of the users overestimate this method and *Purpose* which 20.38% of the users overestimate. Commitment bias describes that people show a tendency to comply with their past behaviour. In the first questionnaire at the beginning of the study, the participants answered a question about the importance of promoting new artists on a scale from 0 to 10. This question implicitly asked the users to commit to promote new artists; this was intended as a base to apply the commitment persuasive strategy. Interestingly, the users thought such a message to be compelling; however, this message was not as effective as the users rated it on the final questionnaire.

The most correctly estimated influential strategies were *Social Influence with mentioning new artist* and *Authority* in which 37% of the users correctly estimate the effectiveness of these methods. Interestingly, users were far more accurate in evaluating the uninfluential strategies. 46.92 % of the users correctly identified *Liking*, and 41.23 % correctly identified *Reciprocity* as an uninfluential strategy. The users' accuracy for these two strategies significantly outperforms the overall users' accuracy. It suggests a *blind spot* or unawareness of the power of influence some strategies have over them. Our results showed the gap between the actual and perceived persuasiveness of different strategies in the context of music recommendation. The discrepancies between the two suggest the presence of cognitive biases in users, exploiting which can have ethical implications.

4.3.2 The Relation Between User demographic characteristics and OCEAN Personalities with the Overestimated or Underestimated Persuasive Strategies

In this section, I explore the relationship between participants' Big 5 (OCEAN) personalities and their ability to predict the effectiveness of the persuasive messages. As in the previous section, I was interested to find out if the participants correctly identified the persuasive message effectiveness. The highest reoccurring overestimating/underestimating/correctly estimating behaviour is considered as the users' dominant behaviour in estimating the effectiveness of a persuasive strategy. Afterward, the behaviour is converted to numbers: underestimating the effectiveness of the persuasive message as 0, correctly estimating the effectiveness as 0.5 and overestimating the effectiveness as 1.

Gender, Age, Favourite Genre

Users with different genders, age and favourite genre in the study did not show any significant difference in their estimating behaviour; therefore, these demographic characteristics do not affect the users' estimation behaviour.

Table 4.10: Percentage of Users' Estimation Behaviour based on Birth Continent

Continent	Correctly Estimated(%)	Under(%)	Over(%)	Number of Users
Africa	80	0	20	5
America	61.6	32.6	5.8	138
Asia	73	16.2	10.8	74
Australia	100	0	0	1
Europe	81.8	9.09	9.09	11

Table 4.11: Percentage of Users' Estimation Behaviour based on Music-Listening Habit

Music-Listening Habit	Correctly Estimated(%)	Under(%)	Over(%)	Number of Users
<1	73.2	14.3	12.5	56
1-3	66.7	29	4.39	114
3>	61.3	29	9.68	62

Birth Continent

Users with different birth continents in the study show a significant difference in their estimating behaviour, especially between two major groups America and Asia (all continents: $\mathcal{P}$=0.02, two major continents:$\mathcal{P}$=0.007). Therefore, different users from different continents do not perform the same. Table 4.10 presents the estimation performance of the users based on their birth continent.

Music Listening Habit

In the preliminary questionnaire, at the beginning of the study, users were prompted about their daily music-listening habit with three options: less than 1 hour, between 1 to 3 hours and more than 3 hours. The results showed that the users with different listening habits do not have the same estimation behaviour $\mathcal{P}$=2.2e$-$16. Table 4.11 demonstrates the estimation performance of the users based on their music-listening habits.

OCEAN Personalities

The correlation between the OCEAN personalities and the participants tendency to over-, under- or correctly estimate the influence of persuasive strategies on them is presented in Figure 4.15 using Kendal rank correlation [41].

The number shown at the beginning of each bar shows the relation's p-value, indicating the relation's significance. Additionally, the red colour shows a negative correlation meaning that the personality leads to underestimation, and the blue colour shows a positive correlation meaning that the personality leads to overestimation. Unfortunately, none of the p-values are significant as none of them are below 0.05. On the other hand, if the p-values were significant, the correlation coefficient is close to 0; therefore, there is no

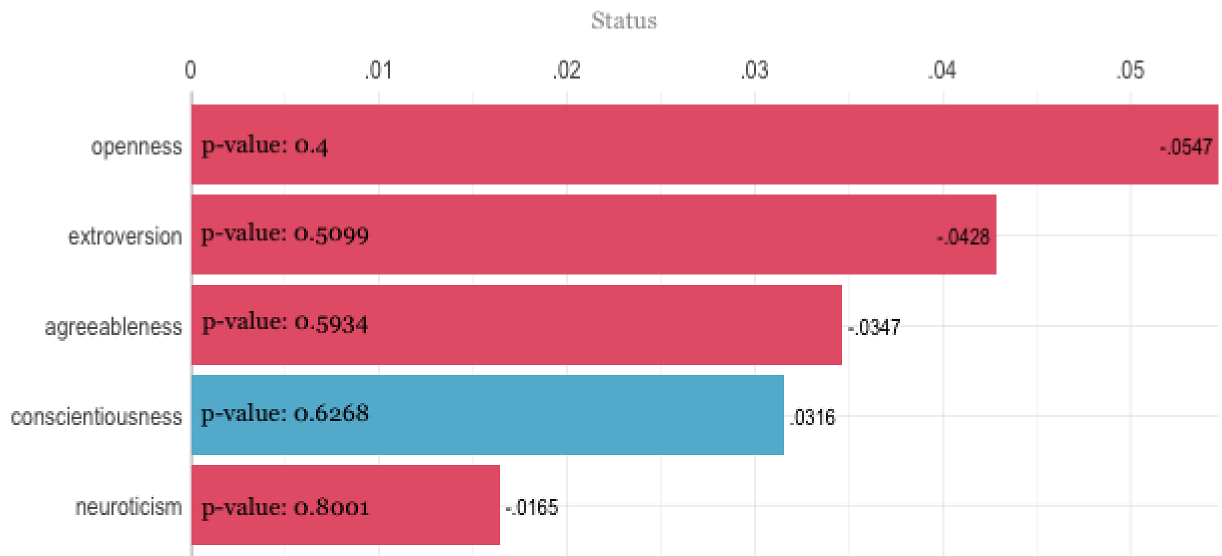


Figure 4.15: Correlation between OCEAN personality traits and overestimating/underestimating the effectiveness of the persuasive messages.

meaningful relation between users' OCEAN personality and their tendency to overestimate or underestimate or correctly estimate the effectiveness of persuasive messages.

5 Conclusion

In this thesis, I researched the efficacy of Cialdini's persuasive strategies for promoting new artists on a fair recommender system for music. This study presented the results of a within-subject study with a system that recommends playlists incorporating songs from famous artists and new little-known artists, in which songs from new artists were accompanied, in some cases, by persuasive messages. Our results show empirical evidence that providing persuasive explanations leads to better ratings of the playlists. Especially mentioning that the unfamiliar songs are from new artists significantly improves the ratings of the playlists. Additionally, our results indicate that ratings of popular songs and songs from new artists are positively correlated to the overall ratings of the playlists. Therefore, there is a need to maintain a certain level of user satisfaction via popular songs to influence the user's satisfaction with the songs of new artists with persuasive messages. Not all of Cialdini's six persuasive strategies are equally effective for promoting new artists. *Authority* and *Social Influence* were the most influential strategies in the experiment. Moreover, based on the study, users with different user demographic characteristics and OCEAN personalities are receptive to distinctive persuasive messages. Therefore, personalizing persuasive messages based on end-user characteristics should be explored to find more effective approaches for promoting recommendations regarding various system stakeholders.

A comparison between the participants' direct ratings of the messages' persuasiveness and the effectiveness of the persuasive messages based on the participants' ratings of the songs from new artists showed that users accuracy in correctly identifying the effect of persuasive messages on themselves was 38.25%. Interestingly, *Scarcity* was the most underestimated method; users consider very low effectiveness for this method. However, the ratings of songs from new artists showed that this method affected users' ratings. As a result, the findings of this study revealed that personalising persuasive strategies solely based on users' perceptions of their receptivity to persuasive strategies may not accurately reflect users' persuasion profiles, and users may underestimate the impact of persuasive strategies on themselves.

The usage of persuasive messages has ethical issues, and a recommender system should avoid deceiving or misusing user trust. For instance, *Authority* is a powerful persuasive strategy, which could impact users' decision process significantly. Therefore, the source of such promotions should be trustworthy, free of financial incentives and solely based on the quality of the songs.

5.1 Contributions

Persuasive strategies are widely deployed to induce users into a specific behaviour, for example, various methods used in the Amazon website to persuade the user to purchase at the earliest convenience [9]. This research explored the effectiveness of Cialdini's persuasive strategies for promoting items recommended with fairness objective. To the best of my knowledge, this thesis is the first to explore the effect of persuasive strategies on promoting fair recommendations. This thesis exhibits the details of the research work to answer the research question *Are persuasive strategies effective for enhancing user satisfaction in a fair(multi-stakeholder) recommender system?*. The contributions of this thesis are:

- A study of users' receptiveness to the persuasive strategies for promoting items recommended based on the fairness objective of the system in a music platform. A persuasive fair mock-up music recommender was developed that promotes songs from new artists using persuasive messages.

- Analysis of the impact of demographics and personalities on the receptiveness of persuasive messages. The thesis examined whether users with different demographic information and personalities have different receptiveness of persuasive messages. The results showed that users with specific demographic characteristics are more receptive to persuasive messages; additionally, users with different OCEAN personality attributes and demographic characteristics are most influenced by different persuasive messages.

- Interpretation of the differences between effective persuasive strategies and the user's ratings of the influence these persuasive messages had on them. Only 66% of the users could correctly identify the effect of persuasive messages on themselves most of the time, and the overall accuracy of the users in evaluating the effect of persuasive strategies was 38.25%, but Empathy and Scarcity were the two most effective methods that the users underestimated.

With this work, we encourage fairness-aware recommenders to utilize persuasive messages to increase user satisfaction of the system while providing adequate exposure for the less-known items in the system. When the user is notified about the nature of the less related or less known items in their recommendation, their satisfaction level is less severely affected. Of course, the usage of persuasive messages can have ethical implications and it should avoid deceiving or misusing user trust. It has to be applied carefully since Users may leave a platform that for the sake of fairness promotes unworthy music. Furthermore, we believe our work opens up a new research direction for exploring the gap between the actual and perceived persuasiveness of different strategies in different domains and contexts. The discrepancies between the two suggest the presence of cognitive biases in users, exploiting which can have ethical implications. Persuasive strategies should be used very carefully to avoid deceiving or misusing user trust.

5.2 Limitations

The study described in this thesis has several limitations. Firstly, the study results were based on a fairly small group of 205 users with open and agreeable personalities. Therefore, these users might have less prejudice to new songs and rate with less bias. Secondly, the designed music recommender recommends playlists were based on the user's chosen favourite genres, rather than on a personalized recommendation based on the user's previous listening behaviour, limits the music recommender's accuracy. Thirdly, this study was conducted in the area of music recommenders, and the results might not be transferable to other areas of recommendation. Finally, the study was conducted in an atypical area for persuasive technology - persuasive recommendation in a multi-stakeholder (or fair) recommender system promoting new artists. The accuracy in users' estimates of persuasiveness might be higher in more typical behaviour change domains, such as exercising or healthy eating behaviour, healthy shopping or learning engagement.

5.3 Future Work

There are a variety of directions to follow up on this thesis work, including the following:

1. The users were presented with playlists based on their favourite genres; they were not personalized. This may have impacted (lowered) the baseline satisfaction of the users with the playlists. Thus, we suggest that future work could incorporate an actual fair recommender algorithm in the system, versus a pre-canned music playlists, tailored to the users' favourite genres and listening history to see if the personalization of the music selections to the user in combination with personalized persuasive messages would result in higher satisfaction and investigate the reliability of such results.

2. With a more accurate recommender, the limit of essential popular songs in a playlist to maintain the effectiveness of persuasive messages could be explored.

3. A fixed message was utilized for liking messages using one of the most famous artists. Personalizing this message based on the user's favourite artist has the potential to increase this persuasive method's efficacy. Moreover, personalizing this message to the user's favourite genre might increase the effect of this message.

4. The effect of personalizing the messages to users' personality could be investigated along with exploring the effect of personality on the efficacy of persuasive messages and playlist balance of new and popular artists.

5. Comparing different implementations (phrasings or visualizations) of the most influential Cialdini's persuasive strategies that we found in this study.

6. For generalizing the study, broadening the scope of "fairness" could be investigated to include not only little known artists, but also artists from different regions, languages.

7. The same approach can be used for fair recommender systems in other areas such as sales or movies.

8. The accuracy in users' estimates of persuasiveness might be higher in more typical behaviour change domains, such as exercising or healthy eating behaviour, healthy shopping or learning engagement. Therefore, we suggest that future work could compare users' perception of effective persuasive strategies with the actual effectiveness of these strategies (measured in behaviour change variables) in other domains, especially since the persuasiveness of persuasive messages is domain-dependent [83].

9. Since our results were obtained via several hypothesis tests throughout the analysis, our results might suffer from the multiple testing problem [12]. *Multiple testing problem* arises when more than one hypothesis is tested at the same time, increasing the risk of making false statistical inferences dramatically. Therefore, future work could adjust the p-value for multiple testing based on the number of the hypothesis tests.

References

[1] Himan Abdollahpouri, Gediminas Adomavicius, Robin Burke, Ido Guy, Dietmar Jannach, Toshihiro Kamishima, Jan Krasnodebski, and Luiz Pizzato. Multistakeholder recommendation: Survey and research directions. *User Modeling and User-Adapted Interaction*, 30(1):127–158, 2020.

[2] Himan Abdollahpouri, Robin Burke, and Masoud Mansoury. Unfair Exposure of Artists in Music Recommendation. *arXiv*, 2020.

[3] Himan Abdollahpouri, Robin Burke, and Bamshad Mobasher. Controlling popularity bias in learning-to-rank recommendation. In *Proceedings of the Eleventh ACM Conference on Recommender Systems*, RecSys '17, page 42–46, New York, NY, USA, 2017. Association for Computing Machinery.

[4] Himan Abdollahpouri, Robin Burke, and Bamshad Mobasher. Recommender systems as multistakeholder environments. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization*, pages 347–348, 2017.

[5] Himan Abdollahpouri, Robin Burke, and Bamshad Mobasher. Managing popularity bias in recommender systems with personalized re-ranking. In *The thirty-second international flairs conference*, 2019.

[6] Himan Abdollahpouri, Masoud Mansoury, Robin Burke, and Bamshad Mobasher. The connection between popularity bias, calibration, and fairness in recommendation. In *Fourteenth ACM Conference on Recommender Systems*, pages 726–731, 2020.

[7] Rediet Abebe, Jon Kleinberg, and David Parkes. Fair division via social comparison. *arXiv preprint arXiv:1611.06589*, 2016.

[8] Ifeoma Adaji, Nafisul Kiron, and Julita Vassileva. Evaluating the susceptibility of e-commerce shoppers to persuasive strategies. a game-based approach. In *International Conference on Persuasive Technology*, pages 58–72. Springer, 2020.

[9] Ifeoma Adaji and Julita Vassileva. Evaluating personalization and persuasion in e-commerce. In *PPT@ PERSUASIVE*, pages 107–113, 2016.

[10] Qingyao Ai, Vahid Azizi, Xu Chen, and Yongfeng Zhang. Learning heterogeneous knowledge base embeddings for explainable recommendation. *Algorithms*, 11(9):137, 2018.

[11] Alejandro Bellogín, Pablo Castells, and Iván Cantador. Statistical biases in information retrieval metrics for recommender systems. *Information Retrieval Journal*, 20(6):606–634, 2017.

[12] Ralf Bender and Stefan Lange. Adjusting for multiple testing—when and how? *Journal of clinical epidemiology*, 54(4):343–349, 2001.

[13] Alex Beutel, Jilin Chen, Tulsee Doshi, Hai Qian, Li Wei, Yi Wu, Lukasz Heldt, Zhe Zhao, Lichan Hong, Ed H Chi, et al. Fairness in recommendation ranking through pairwise comparisons. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 2212–2220, 2019.

[14] Asia J Biega, Krishna P Gummadi, and Gerhard Weikum. Equity of attention: Amortizing individual fairness in rankings. In *The 41st international acm sigir conference on research & development in information retrieval*, pages 405–414, 2018.

[15] Robin Burke. Multisided Fairness for Recommendation. *arXiv*, 2017.

[16] Robin Burke, Nasim Sonboli, and Aldo Ordonez-Gauger. Balanced neighborhoods for multi-sided fairness in recommendation. In *Conference on Fairness, Accountability and Transparency*, pages 202–214. PMLR, 2018.

[17] Victor R Basili1 Gianluigi Caldiera and H Dieter Rombach. The goal question metric approach. *Encyclopedia of software engineering*, pages 528–532, 1994.

[18] Òscar Celma and Pedro Cano. From hits to niches? or how popular artists can bias music recommendation and discovery. In *Proceedings of the 2nd KDD Workshop on Large-Scale Recommender Systems and the Netflix Prize Competition*, pages 1–8, 2008.

[19] Weiyu Cheng, Yanyan Shen, Linpeng Huang, and Yanmin Zhu. Incorporating interpretability into latent factor models via fast influence analysis. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 885–893, 2019.

[20] Robert Cialdini. *Pre-suasion: A revolutionary way to influence and persuade*. Simon and Schuster, 2016.

[21] Robert B Cialdini. The science of persuasion. *Scientific American*, 284(2):76–81, 2001.

[22] Ana Ciocarlan, Judith Masthoff, and Nir Oren. Actual persuasiveness: impact of personality, age and gender on message type susceptibility. In *International Conference on Persuasive Technology*, pages 283–294. Springer, 2019.

[23] Edward L Deci. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist*, 55(1):68–78, 2000.

[24] Otis Dudley Duncan. Path analysis: Sociological examples. *American journal of Sociology*, 72(1):1–16, 1966.

[25] Daniel Ellsberg. Risk, ambiguity, and the savage axioms. *The quarterly journal of economics*, pages 643–669, 1961.

[26] Golnoosh Farnadi, Pigi Kouki, Spencer K Thompson, Sriram Srinivasan, and Lise Getoor. A fairness-aware hybrid recommender system. *arXiv preprint arXiv:1809.09030*, 2018.

[27] Bruce Ferwerda, Kevin Swelsen, and Emily Yang. Explaining content-based recommendations. *New York*, pages 1–24, 2018.

[28] Brian J Fogg. Persuasive technology: using computers to change what we think and do. *Ubiquity*, 2002(December):2, 2002.

[29] Fatih Gedikli, Dietmar Jannach, and Mouzhi Ge. How should i explain? a comparison of different explanation types for recommender systems. *International Journal of Human-Computer Studies*, 72(4):367–382, 2014.

[30] Sofia Gkika and George Lekakos. The persuasive role of explanations in recommender systems. In *BCSS PERSUASIVE*, pages 59–68, 2014.

[31] Lewis R Goldberg. The structure of phenotypic personality traits. *American psychologist*, 48(1):26, 1993.

[32] Jonathan L Herlocker, Joseph A Konstan, and John Riedl. Explaining collaborative filtering recommendations. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work*, pages 241–250, 2000.

[33] Jacob B Hirsh, Sonia K Kang, and Galen V Bodenhausen. Personalized persuasion: Tailoring persuasive appeals to recipients' personality traits. *Psychological science*, 23(6):578–581, 2012.

[34] Rick H Hoyle. *Structural equation modeling: Concepts, issues, and applications*. Sage, 1995.

[35] Dietmar Jannach, Markus Zanker, Alexander Felfernig, and Gerhard Friedrich. *Recommender systems: an introduction*. Cambridge University Press, 2010.

[36] Oliver P John, Sanjay Srivastava, et al. The big five trait taxonomy: History, measurement, and theoretical perspectives. *Handbook of personality: Theory and research*, 2(1999):102–138, 1999.

[37] Toshihiro Kamishima, Shotaro Akaho, Hideki Asoh, and Jun Sakuma. Correcting popularity bias by enhancing recommendation neutrality. In *RecSys Posters*, 2014.

[38] Toshihiro Kamishima, Shotaro Akaho, Hideki Asoh, and Issei Sato. Model-based approaches for independence-enhanced recommendation. In *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*, pages 860–867. IEEE, 2016.

[39] Maurits Kaptein, Boris De Ruyter, Panos Markopoulos, and Emile Aarts. Adaptive persuasive systems: A study of tailored persuasive text messages to reduce snacking. *ACM Trans. Interact. Intell. Syst.*, 2(2), jun 2012.

[40] Kathy Kellermann and Tim Cole. Classifying Compliance Gaining Messages: Taxonomic Disorder and Strategic Confusion. *Communication Theory*, 4(1):3–60, 03 2006.

[41] Maurice George Kendall. Rank correlation methods. 1948.

[42] Pigi Kouki, James Schaffer, Jay Pujara, John O'Donovan, and Lise Getoor. Personalized explanations for hybrid recommender systems. In *Proceedings of the 24th International Conference on Intelligent User Interfaces*, pages 379–390, 2019.

[43] Dominik Kowald, Markus Schedl, and Elisabeth Lex. The unfairness of popularity bias in music recommendation: A reproducibility study, 2019.

[44] William H Kruskal and W Allen Wallis. Use of ranks in one-criterion variance analysis. *Journal of the American statistical Association*, 47(260):583–621, 1952.

[45] Renaud Lambiotte and Michal Kosinski. Tracking the digital footprints of personality. *Proceedings of the IEEE*, 102(12):1934–1939, 2014.

[46] Howard Levene. Robust tests for equality of variances. *Contributions to probability and statistics. Essays in honor of Harold Hotelling*, pages 279–292, 1961.

[47] Mark Levy and Klaas Bosteels. Music recommendation and the long tail. In *1st Workshop On Music Recommendation And Discovery (WOMRAD), ACM RecSys, 2010, Barcelona, Spain*. Citeseer, 2010.

[48] Weiwen Liu, Jun Guo, Nasim Sonboli, Robin Burke, and Shengyu Zhang. Personalized fairness-aware re-ranking for microlending. In *Proceedings of the 13th ACM Conference on Recommender Systems*, pages 467–471, 2019.

[49] Anne Marike Lokhorst, Carol Werner, Henk Staats, Eric van Dijk, and Jeff L Gale. Commitment and behavior change: A meta-analysis and critical review of commitment-making strategies in environmental research. *Environment and behavior*, 45(1):3–34, 2013.

[50] William W Maddux, Elizabeth Mullen, and Adam D Galinsky. Chameleons bake bigger pies and take bigger pieces: Strategic behavioral mimicry facilitates negotiation outcomes. *Journal of Experimental Social Psychology*, 44(2):461–468, 2008.

[51] Millecamp Martijn, Cristina Conati, and Katrien Verbert. "knowing me, knowing you": personalized explanations for a music recommender system. *User Modeling and User-Adapted Interaction*, pages 1–38, 2022.

[52] Robert R McCrae and Oliver P John. An introduction to the five-factor model and its applications. *Journal of personality*, 60(2):175–215, 1992.

[53] Rishabh Mehrotra, James McInerney, Hugues Bouchard, Mounia Lalmas, and Fernando Diaz. Towards a fair marketplace: Counterfactual evaluation of the trade-off between relevance, fairness & satisfaction in recommendation systems. *International Conference on Information and Knowledge Management, Proceedings*, pages 2243–2252, 2018.

[54] Stanley Milgram. Behavioral study of obedience. *The Journal of abnormal and social psychology*, 67(4):371, 1963.

[55] Martijn Millecamp, Nyi Nyi Htun, Cristina Conati, and Katrien Verbert. To explain or not to explain: the effects of personal characteristics when explaining music recommendations. In *Proceedings of the 24th International Conference on Intelligent User Interfaces*, pages 397–407, 2019.

[56] Martijn Millecamp, Nyi Nyi Htun, Cristina Conati, and Katrien Verbert. What's in a user? towards personalising transparency for music recommender interfaces. In *Proceedings of the 28th ACM Conference on User Modeling, Adaptation and Personalization*, pages 173–182, 2020.

[57] Daniel Müllensiefen, Bruno Gingras, Jason Musil, and Lauren Stewart. The musicality of non-musicians: an index for assessing musical sophistication in the general population. *PloS one*, 9(2):e89642, 2014.

[58] Mark Mulligan. Superstar economics, Mar 2014.

[59] Xia Ning and George Karypis. Slim: Sparse linear methods for top-n recommender systems. In *2011 IEEE 11th international conference on data mining*, pages 497–506. IEEE, 2011.

[60] Rita Orji, Regan L Mandryk, and Julita Vassileva. Gender, age, and responsiveness to cialdini's persuasion strategies. In *International Conference on Persuasive Technology*, pages 147–159. Springer, 2015.

[61] Rita Orji, Regan L Mandryk, and Julita Vassileva. Improving the efficacy of games for change using personalization models. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 24(5):1–22, 2017.

[62] Rita Orji, Julita Vassileva, and Regan L Mandryk. Lunchtime: a slow-casual game for long-term dietary behavior change. *Personal and ubiquitous computing*, 17(6):1211–1221, 2013.

[63] Rita Orji, Julita Vassileva, and Regan L Mandryk. Modeling the efficacy of persuasive strategies for different gamer types in serious games for health. *User Modeling and User-Adapted Interaction*, 24(5):453–498, 2014.

[64] Kiemute Oyibo, Ifeoma Adaji, Rita Orji, Babatunde Olabenjo, and Julita Vassileva. Susceptibility to persuasive strategies: a comparative analysis of nigerians vs. canadians. In *Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization*, pages 229–238, 2018.

[65] Kiemute Oyibo, Ifeoma Adaji, Rita Orji, and Julita Vassileva. The susceptibility of africans to persuasive strategies: A case study of nigeria. *PPT@ PERSUASIVE*, 2018:8–21, 2018.

[66] Kiemute Oyibo, Ifeoma Adaji, and Julita Vassileva. Social cognitive determinants of exercise behavior in the context of behavior modeling: a mixed method approach. *Digital health*, 4:2055207618811555, 2018.

[67] Kiemute Oyibo, Rita Orji, and Julita Vassileva. Investigation of the influence of personality traits on cialdini's persuasive strategies. *PPT@ PERSUASIVE*, 2017:8–20, 2017.

[68] Kiemute Oyibo and Julita Vassileva. Homex: Persuasive technology acceptance model and the moderating effect of culture. *Frontiers in Computer Science*, 2:10, 2020.

[69] Daniel J O'Keefe. Message Pretesting Using Assessments of Expected or Perceived Persuasiveness: Evidence About Diagnosticity of Relative Actual Persuasiveness. *Journal of Communication*, 68(1):120–142, 02 2018.

[70] Yoon-Joo Park and Alexander Tuzhilin. The long tail of recommender systems and how to leverage it. In *Proceedings of the 2008 ACM conference on Recommender systems*, pages 11–18, 2008.

[71] Paolo Pilloni, Luca Piras, Salvatore Carta, Gianni Fenu, Fabrizio Mulas, and Ludovico Boratto. Recommender system lets coaches identify and help athletes who begin losing motivation. *Computer*, 51(3):36–42, 2018.

[72] Zhaochun Ren, Shangsong Liang, Piji Li, Shuaiqiang Wang, and Maarten de Rijke. Social collaborative viewpoint regression with explainable recommendations. In *Proceedings of the tenth ACM international conference on web search and data mining*, pages 485–494, 2017.

[73] Francesco Ricci, Lior Rokach, and Bracha Shapira. Introduction to recommender systems handbook. In *Recommender systems handbook*, pages 1–35. Springer, 2011.

[74] Sherwin Rosen. The economics of superstars. *The American economic review*, 71(5):845–858, 1981.

[75] Henry Scheffe. *The analysis of variance*, volume 72. John Wiley & Sons, 1999.

[76] Sungyong Seo, Jing Huang, Hao Yang, and Yan Liu. Interpretable convolutional neural networks with dual local and global attention for review rating prediction. In *Proceedings of the eleventh ACM conference on recommender systems*, pages 297–305, 2017.

[77] Jingzhi Shang, Debra Z Basil, and Walter Wymer. Using social marketing to enhance hotel reuse programs. *Journal of Business Research*, 63(2):166–172, 2010.

[78] Samuel Sanford Shapiro and Martin B Wilk. An analysis of variance test for normality (complete samples). *Biometrika*, 52(3/4):591–611, 1965.

[79] Gkika Sofia, Skiada Marianna, Lekakos George, and Kourouthanasis Panos. Investigating the role of personality traits and influence strategies on the persuasive effect of personalized recommendations. In *4th Workshop on emotions and personality in personalized systems (EMPIRE)*, volume 9, 2016.

[80] Nasim Sonboli, Jessie J Smith, Florencia Cabral Berenfus, Robin Burke, and Casey Fiesler. Fairness and transparency in recommendation: The users' perspective. In *Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization*, pages 274–279, 2021.

[81] Spotify. Spotify — Company Info, 04 2021.

[82] David B Strohmetz, Bruce Rind, Reed Fisher, and Michael Lynn. Sweetening the till: the use of candy to increase restaurant tipping 1. *Journal of Applied Social Psychology*, 32(2):300–309, 2002.

[83] Rosemary J Thomas, Judith Masthoff, and Nir Oren. Can i influence you? development of a scale to measure perceived persuasiveness and two studies showing the use of the scale. *Frontiers in Artificial Intelligence*, 2:24, 2019.

[84] Nava Tintarev and Judith Masthoff. A survey of explanations in recommender systems. In *2007 IEEE 23rd international conference on data engineering workshop*, pages 801–810. IEEE, 2007.

[85] Frank Wilcoxon. Individual comparisons by ranking methods. In *Breakthroughs in statistics*, pages 196–202. Springer, 1992.

[86] Martin B Wilk and Ram Gnanadesikan. Probability plotting methods for the analysis for the analysis of data. *Biometrika*, 55(1):1–17, 1968.

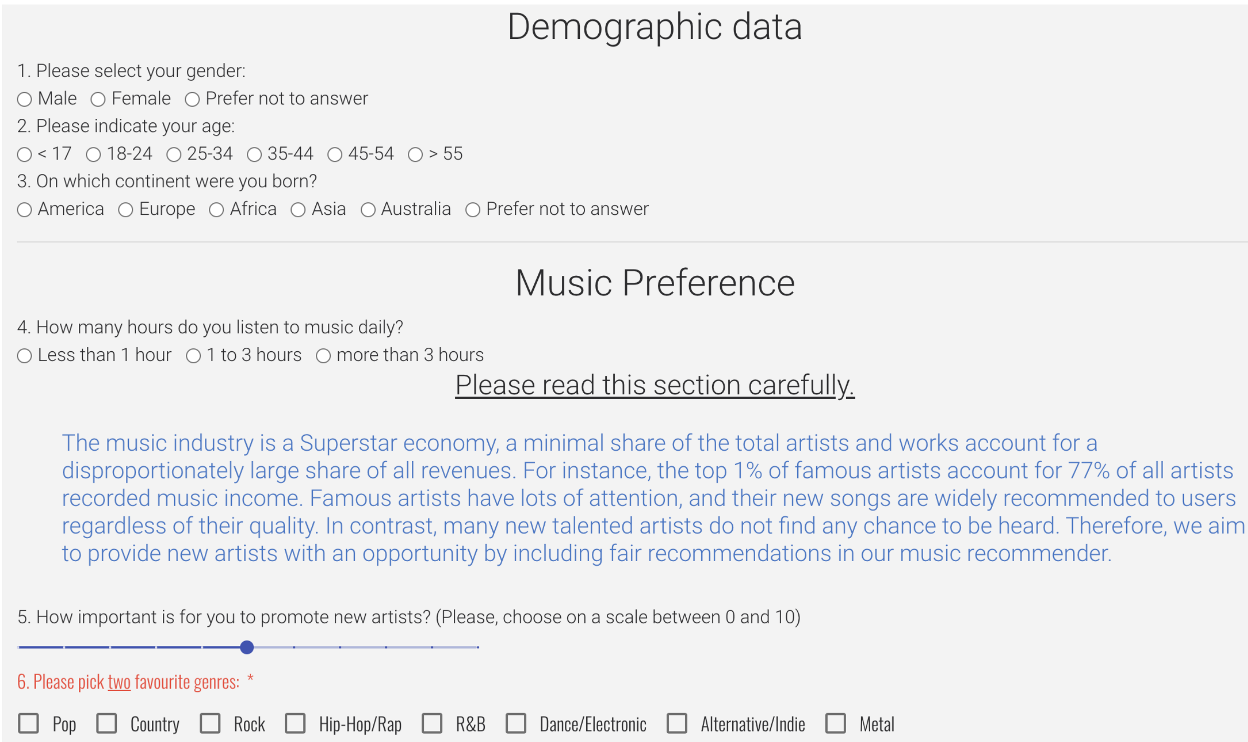
[87] David F Williamson, Robert A Parker, and Juliette S Kendrick. The box plot: a simple visual method to interpret data. *Annals of internal medicine*, 110(11):916–921, 1989.

[88] Sirui Yao and Bert Huang. Beyond parity: Fairness objectives for collaborative filtering. *arXiv preprint arXiv:1705.08804*, 2017.

[89] Yongfeng Zhang, Guokun Lai, Min Zhang, Yi Zhang, Yiqun Liu, and Shaoping Ma. Explicit factor models for explainable recommendation based on phrase-level sentiment analysis. In *Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval*, pages 83–92, 2014.

Appendix A

Preliminary Questionnaire



Demographic data

1. Please select your gender:

○ Male ○ Female ○ Prefer not to answer

2. Please indicate your age:

○ < 17 ○ 18-24 ○ 25-34 ○ 35-44 ○ 45-54 ○ > 55

3. On which continent were you born?

○ America ○ Europe ○ Africa ○ Asia ○ Australia ○ Prefer not to answer

Music Preference

4. How many hours do you listen to music daily?

○ Less than 1 hour ○ 1 to 3 hours ○ more than 3 hours

Please read this section carefully.

The music industry is a Superstar economy, a minimal share of the total artists and works account for a disproportionately large share of all revenues. For instance, the top 1% of famous artists account for 77% of all artists recorded music income. Famous artists have lots of attention, and their new songs are widely recommended to users regardless of their quality. In contrast, many new talented artists do not find any chance to be heard. Therefore, we aim to provide new artists with an opportunity by including fair recommendations in our music recommender.

5. How important is for you to promote new artists? (Please, choose on a scale between 0 and 10)

6. Please pick two favourite genres: *

☐ Pop ☐ Country ☐ Rock ☐ Hip-Hop/Rap ☐ R&B ☐ Dance/Electronic ☐ Alternative/Indie ☐ Metal

Figure A.1: Preliminary Questionnaire

Appendix B

Big Five Personality Test

The Big Five Personality Test

from personality-testing.info
courtesy ipip.ori.org

Introduction

This is a personality test, it will help you understand why you act the way that you do and how your personality is structured. Please follow the instructions below, scoring and results are on the next page.

Instructions

In the table below, for each statement 1-50 mark how much you agree with on the scale 1-5, where 1=disagree, 2=slightly disagree, 3=neutral, 4=slightly agree and 5=agree, in the box to the left of it.

Test

Rating	I....	Rating	I.....
	1. Am the life of the party.		26. Have little to say.
	2. Feel little concern for others.		27. Have a soft heart.
	3. Am always prepared.		28. Often forget to put things back in their proper place.
	4. Get stressed out easily.		29. Get upset easily.
	5. Have a rich vocabulary.		30. Do not have a good imagination.
	6. Don't talk a lot.		31. Talk to a lot of different people at parties.
	7. Am interested in people.		32. Am not really interested in others.
	8. Leave my belongings around.		33. Like order.
	9. Am relaxed most of the time.		34. Change my mood a lot.
	10. Have difficulty understanding abstract ideas.		35. Am quick to understand things.
	11. Feel comfortable around people.		36. Don't like to draw attention to myself.
	12. Insult people.		37. Take time out for others.
	13. Pay attention to details.		38. Shirk my duties.
	14. Worry about things.		39. Have frequent mood swings.
	15. Have a vivid imagination.		40. Use difficult words.
	16. Keep in the background.		41. Don't mind being the center of attention.
	17. Sympathize with others' feelings.		42. Feel others' emotions.
	18. Make a mess of things.		43. Follow a schedule.
	19. Seldom feel blue.		44. Get irritated easily.
	20. Am not interested in abstract ideas.		45. Spend time reflecting on things.
	21. Start conversations.		46. Am quiet around strangers.
	22. Am not interested in other people's problems.		47. Make people feel at ease.
	23. Get chores done right away.		48. Am exacting in my work.
	24. Am easily disturbed.		49. Often feel blue.
	25. Have excellent ideas.		50. Am full of ideas.

E = 20 + (1) ____ - (6) ____ + (11) ____ - (16) ____ + (21) ____ - (26) ____ + (31) ____ - (36) ____ + (41) ____ - (46) ____ = ______

A = 14 - (2) ____ + (7) ____ - (12) ____ + (17) ____ - (22) ____ + (27) ____ - (32) ____ + (37) ____ + (42) ____ + (47) ____ = ______

C = 14 + (3) ____ - (8) ____ + (13) ____ - (18) ____ + (23) ____ - (28) ____ + (33) ____ - (38) ____ + (43) ____ + (48) ____ = ______

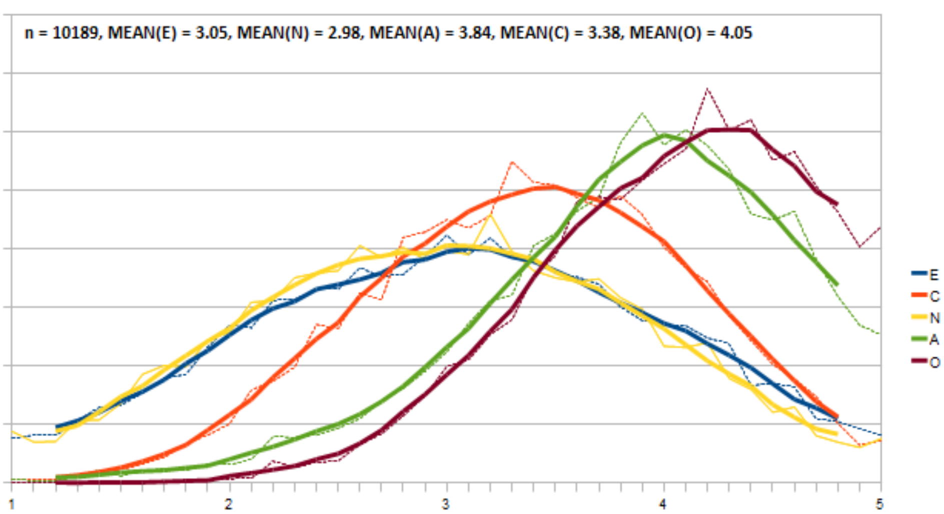
N = 38 - (4) ____ + (9) ____ - (14) ____ + (19) ____ - (24) ____ - (29) ____ - (34) ____ - (39) ____ - (44) ____ - (49) ____ = ______

O = 8 + (5) ____ - (10) ____ + (15) ____ - (20) ____ + (25) ____ - (30) ____ + (35) ____ + (40) ____ + (45) ____ + (50) ____ = ______

The scores you calculate should be between zero and forty. Below is a description of each trait.

- **Extroversion (E)** is the personality trait of seeking fulfillment from sources outside the self or in community. High scorers tend to be very social while low scorers prefer to work on their projects alone.
- **Agreeableness (A)** reflects much individuals adjust their behavior to suit others. High scorers are typically polite and like people. Low scorers tend to 'tell it like it is'.
- **Conscientiousness (C)** is the personality trait of being honest and hardworking. High scorers tend to follow rules and prefer clean homes. Low scorers may be messy and cheat others.
- **Neuroticism (N)** is the personality trait of being emotional.
- **Openness to Experience (O)** is the personality trait of seeking new experience and intellectual pursuits. High scores may day dream a lot. Low scorers may be very down to earth.

Below is a graph of how other people scored when test was offered on the internet.



Appendix C

Final Questionnaire

Feedback

1. How would you rate your overall experience with this music recommender?

○ Strongly unsatisfactory ○ Unsatisfactory ○ Neutral ○ Satisfactory ○ Strongly satisfactory

2. How fair do you find this system?

○ Extremely unfair ○ Unfair ○ Neutral ○ Somewhat fair ○ Extremely fair

3. How much do you believe in the trustfulness of this music recommender?

○ Extremely untrustworthy ○ Untrustworthy ○ Neutral ○ Somewhat trustworthy ○ Completely trustworthy

4. How transparent is this recommender? [Did you understand why you get these recommendations?]

○ Extremely untransparent ○ Untransparent ○ Neutral ○ Somewhat transparent ○ Completely transparent

5. How likely is it that you would recommend the fair items[songs from little-known artists] to a friend or a colleague? (0-10)

6. Please rate the following persuasive messages based on the criteria below:

★ Not influential at all ★★ Not Influential ★★★ Neutral

★★★★Influential ★★★★★ Strongly Influential

- This song is included to give new artists a chance to be listened to. ★★★★★
- Experts have recommended this new little-known artist. ★★★★★
- This song is included because you agreed to have fair recommendations. ★★★★★
- 75% of new artists don't find a chance to become famous despite being good. ★★★★★
- Drake has suggested this new artist providing a chance to become popular. ★★★★★
- Thanks for using our fair recommender. ★★★★★
- This song is only available for a limited time. ★★★★★
- This song is only available for a limited time to promote this new artist. ★★★★★
- 80% of our users have listened to this song. ★★★★★
- 80% of our users have listened to this song from this new artist. ★★★★★

Figure C.1: Final Questionnaire

Appendix D

Ethics Approval Certificate

UNIVERSITY OF SASKATCHEWAN

Behavioural Research Ethics Board (Beh-REB) 02/Oct/2020

Certificate of Approval

Application ID:	2260
Principal Investigator:	Julita Vassileva
Department:	Department of Computer Science
Locations Where Research Activities are Conducted:	Online survey, Canada
Student(s):	Seyedeh Mina Mousavifar
Funder(s):	Natural Sciences and Engineering Research Council of Canada
Sponsor:	Natural Sciences and Engineering Research Council of Canada
Title:	Evaluating the efficacy of persuasive strategies for promoting fair recommendations
Approved On:	02/Oct/2020
Expiry Date:	02/Oct/2021
Approval Of:	Behavioural Research Ethics Application Consent Form First Questionnaire Final Questionnaire Big-five Personality Test Recruitment Form
Acknowledgment Of:	
Review Type:	Delegated Review

CERTIFICATION

The University of Saskatchewan Behavioural Research Ethics Board (Beh-REB) is constituted and operates in accordance with the current version of the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TPCS 2 2018). The University of Saskatchewan Behavioural Research Ethics Board has reviewed the above-named project. The proposal was found to be acceptable on ethical grounds. The principal investigator has the responsibility for any other administrative or regulatory approvals that may pertain to this project, and for ensuring that the authorized project is carried out according to the conditions outlined in the original protocol submitted for ethics review. This Certificate of Approval is valid for the above time period provided there is no change in experimental protocol or consent process or documents.

Any significant changes to your proposed method, or your consent and recruitment procedures should be reported to the Chair for Research Ethics Board consideration in advance of its implementation.

ONGOING REVIEW REQUIREMENTS

In order to receive annual renewal, a status report must be submitted to the REB Chair for Board consideration within one month prior to the current expiry date each year the project remains open, and upon project completion. Please refer to the following website for further instructions: https://vpresearch.usask.ca/researchers/forms.php.

Digitally Approved by Patricia Simonson
Vice-Chair, Behavioural Research Ethics Board
University of Saskatchewan

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