Understanding User Trust in Different Recommenders and Smartphone Applications

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Abstract. In recent times, we are witnessing rapid growth in smartphone applications due to various types of services ranging from bank transactions to health and well-being monitoring, that these apps are providing. However, most often these apps suffer from low user trust and that directly impacts the utility and adherence to the apps. Thereby, it is crucial to understand the user trust in different types of apps and recommenders to improve the utility and adherence of the apps. In this work, we perform a detailed investigation of user trust in four major types of apps, including health apps, payment apps, news apps, and gaming apps, and four major groups of recommenders, i.e., friends, family members, external recommenders (healthcare providers, news channels, or advertisements), and no recommender. From our detailed analysis of a study with 60 smartphone users with different backgrounds, we find a higher trust in health apps and payment apps when recommended by healthcare providers or physicians, and friends or family members. In general, we do not find any significant differences among users with different backgrounds. Thereby, we recommend considering specific groups of recommenders and their recommended features while developing relevant apps to achieve higher utility and adherence.

Keywords: Smartphone app · Recommenders · User trust

1 Introduction

1.1 Motivation

Due to the rise of sensing power and computing capability of smartphones and advancement in mobile networks [8], major app stores, including Google Play, Apple App Store, and Amazon Appstore, are flooded with more than 3.48 million apps [5] providing various services, including discovering places of interest [35,41,43,46,47], security and user authentication [11–13,20,29,31,38–40,44,45], assessing respiratory diseases and their stages [14,26,28,49,50], assessing

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health and wellbeing [10,22,27,33,34,36,37,42,48], and call behavior assessment [15,18,30,32]. The global market for smartphone applications is expected to grow by 11.5% compound annual growth rate (CAGR) from 2020 to 2027 [6]. With the increase of smartphone apps, we are experiencing an increased number of downloads, i.e., a 7% rise in 2021 compared to 2020 [4]. Among various types of app that people download and use, mobile health (mHealth) apps, news apps, gaming apps, and payment apps are found to be the most common types [1].

The global market for mobile health (mHealth) apps is predicted to increase at a CAGR of 11.8% from 2022 to 2030 [2]. This rapid increase in the adoption of mHealth apps is due to the various benefits, including real-time and remote patient monitoring, diagnosis, and treatment based on physicians' recommendations, that the mHealth apps provide to the users [3]. During the COVID-19 global pandemic, around 900 million new mobile payment apps were added to the App stores (in 2020), most of which are primarily targeted to help users make online payments [7]. However, a user's decision to use an app from a set of apps could affect the user's trust in people who are recommending the app. Thereby, knowing users' trust in different recommenders can help the app designer and developer involve the specific group of recommenders to develop apps with a higher utility and adherence.

1.2 Related Work

Since the compliance of smartphone apps drop over time, researchers have been actively trying to find factors that affect a user's trust in apps in order to improve the compliance and utility of the apps. Along this line, a group of researchers has investigated the popularity of different categories of mobile applications using *monthly active users* (MAUs) [23]. They have analyzed important features of mobile apps and their association with global market share and growth rate. Another group of researchers has tried to determine the variables that lead to shorter *application life cycles* (ALCs) of an app [25]. Researchers have found several factors, including telecommunication infrastructure, smartphone hardware specifications, application user interfaces, data privacy, security, trends, and ads that affect a user's choice to install and continue specific smartphone apps. Additionally, some researchers have found attractiveness, value, ease-of-use, trust, social support, diffusiveness, and user reviews are some key elements that influence users' decisions to download and utilize apps from the vast choices accessible in the app stores [9,16,19].

To better understand different factors and their impact on app compliance, several focused studies have been conducted with specific categories of apps, such as news apps, gaming apps, health apps, social networking apps, payment apps, and many other apps [17,21,24,51–53]. While some researchers investigated the major user concerns in using a social networking app [51], some found perceived performance risk, perceived financial risk, and perceived privacy risk have strong negative effects on perceived value and acceptance of payment apps [52]. Similarly, some researchers have found user experience and functionality of a health app as the main factors affecting a user's decision to continue using an app [24].

Additionally, some researchers have found the popularity of the apps and the security preferences of the users as key features to affect a user's decision to continue an app [53]. However, none of these works thoroughly investigated user trust in different types of recommender groups, such as family members, friends, and physicians, and their association with various types of apps based on users' backgrounds.

1.3 Contribution

The main contribution of this work is to understand user trust in different types of smartphone applications and recommenders. Also, we investigate whether there is any significant difference in trust among different group of app users. While we find a high level of user trust in health apps and payment apps compared to other types of apps when the apps are recommended by healthcare providers, friends, or family members, we do not find any statistically significant difference among different groups of users based on educational background, age, app development experience, and gender. Therefore, our findings are generalized to the entire population, and we recommend bringing the respective group of recommenders into the design process of different types of smartphone apps, including health and payment apps. Thereby, the apps can be developed based on various features that the recommenders think to better serve the respective users. This way the apps will have a higher chance of serving the targeted user population.

Organization: First, we present our human study data collection approach, followed by our methods to analyze the collected data in the "Approach" section (Sect. 2). Next, in "Analysis" section (Sect. 3), we present our detailed analysis using graphical and statistical techniques to determine user-trust in different recommenders and smartphone apps and to determine statistical significance of different factors, such as app development experience, age, education level, gender, and marital status. In the end, we present the conclusions in the "Conclusions" section (Sect. 4) and the limitations and future work in the "Limitations and Future Work" section (Sect. 5).

2 Approach

First, we present our human study data collection approach, followed by our methods to analyze the collected data and determine user-trust towards different types of smartphone applications and recommendation groups.

2.1 Human Study Data Collection

To understand the significance of recommender groups on a users' trust towards different types of apps, we conduct a study that is approved by the institutional review board (IRB#: IRB-2022-156). To reach out to different smartphone user

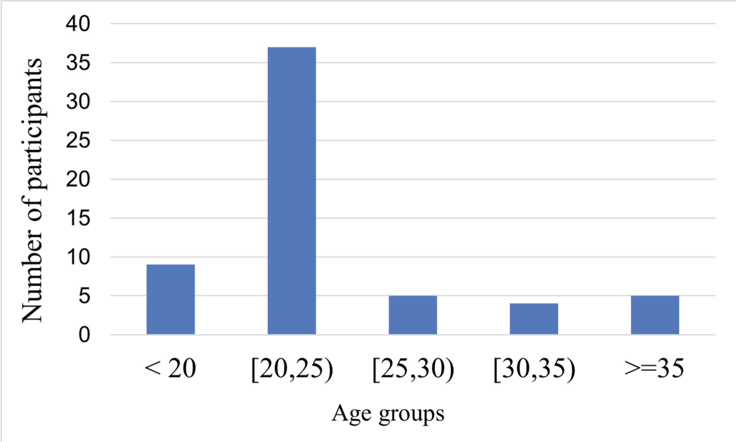

Fig. 1. Bar graphs presenting subject distribution based on age

groups, we post our flyers to various online groups in different social media platforms, such as Twitter and Facebook, in addition to posting on university advertisement boards. The flyer contains a QR code to a Google Form survey that we use to collect data. Participants can reach to the survey from the QR code posted on the flyer and participants can submit their responses anonymously without providing any email id, phone number, or person identifiable information (PPI). Additionally, participation in the survey was completely voluntary and participants could withdraw from the study any time they want while taking the survey. In the "Participant Demographics" section (Sect. 2.1), we present the demographic details of our study subjects. During the study, we use Google Form surveys to anonymously collect various demographic information about subjects, including gender and age, with some additional questions to inquire about subjects' marital status, educational background, and smartphone app development experience. To understand a users' trust towards different recommender groups and smartphone applications, we ask additional questions as discussed in the "Survey" section (Sect. 2.1).

Participant Demographics We were able to get replies from 60 anonymous participants throughout the experiment. There are 60 participants, and 65.9% of them are men. The total subject pool is divided into five age groups: 20, [20, 25], [25, 30], [30, 35], and $\geq$35. Figure 1 shows that the dominant age range is [20, 25] years, where 62% of the participants are found.

Since a subject's marital status may affect that subject's trust in various recommender groups, including family, we additionally collected the participants' marital status during the study. We discovered that 51 of the total 60 participants are single. We display the subjects' educational backgrounds in Fig. 2. We discover that 36.4% participants have completed their undergrad (termed as

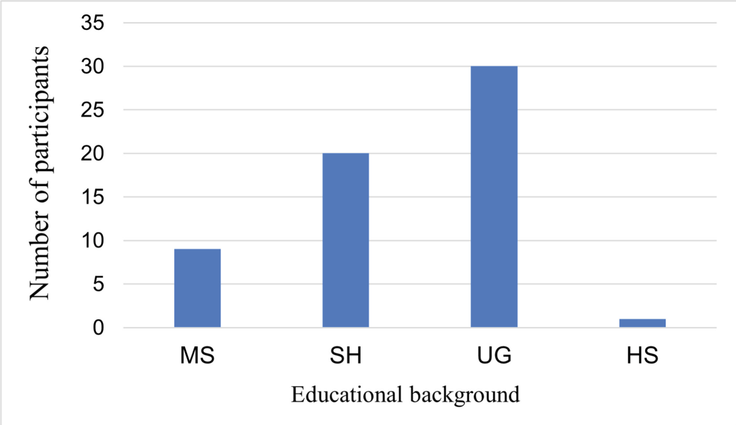

Fig. 2. Bar graphs presenting subject distribution based on educational background

UG in the figure), 43.2% have completed their senior high school, 18.2% have earned a master's degree, and the other participants have completed high school (termed as HS in the figure).

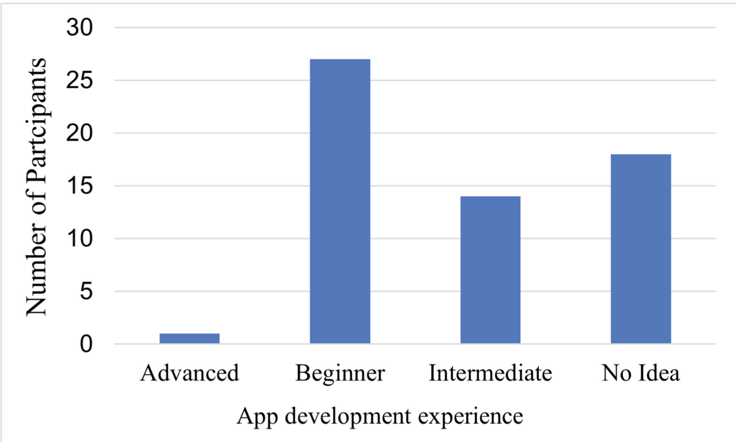

Fig. 3. Bar graphs presenting subject distribution based on app development experience

Additionally, we ask the subjects to report their smartphone app development experience (Fig. 3). Only 2.3% of the subjects had advanced experience, and 25% of the participants have no prior understanding of app development.

Table 1. Different types of smartphone apps

Types of Apps	Acronyms
Health App	H
Gaming App	G
News App	N
Payment App	P

Survey. During the study, we investigate user-trust across four major types of smartphone applications as presented in Table 1. And, participants respond to the following four questions:

1. How frequently do you install a Health app recommended by the following groups?
2. How frequently do you install an online Payment app recommended by the following groups?
3. How frequently do you install a News app (app that provides all the latest news) recommended by the following groups?
4. How frequently do you install a Gaming app recommended by the following groups?

For each app type (i.e., one of the above four questions), subjects rate their trust in different apps when they are recommended by the following four major groups:

- Friends
- Family Members
- External Recommenders (i.e., physicians or healthcare providers (H apps), news channels (N apps), or advertisements (P and G apps)
- No Recommendation

Where the "external recommender" is a term we introduced while analyzing and presenting our findings, but during the study we present them as showed inside the parenthesis based on the app type. Additionally, the "no recommendation" refers to cases where the users do not have any recommender group. Participants rate the recommender groups on a scale of 1 to 5 for each of the four app types mentioned above. A rating of 1 means a recommender group is trusted the least, and 5 means the highest level of trust.

2.2 Methods

In this work, we consider a two-step approach to analyze our data. We first utilize a visualization-based approach using stacked-bars to find user-trust variations across different types of smartphone applications and recommender groups. Next, we use statistical tests, such as the $z-test$ and χ^2-test, to determine the

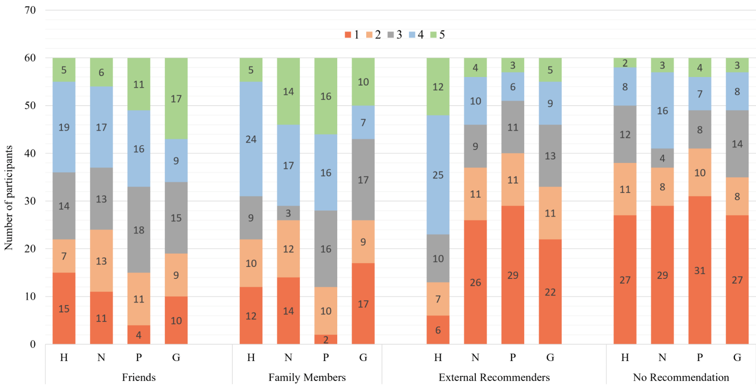

Fig. 4. User-trust rating across different types of smartphone apps and recommender groups, where 1 and 5 mean the lowest and highest level of trust

statistical significance of different features, such as educational background, age, app development experience, marital status, and gender, on user-trust across different types of apps and recommender groups.

3 Analysis

While interpreting a user's trust, i.e., willingness to use an app based on a specific recommender group, we group ratings 1 and 2 into "least likely" (i.e., low trust) category. Similarly, we group ratings 4 and 5 to "highly likely" (i.e., high trust) category. In Fig. 4, we use stacked bars to present users' rating across different types of recommenders and smartphone apps.

We first analyze **friends** as a recommender group and try to determine user-trust across different types of apps when they are recommended by friends. In the figure, we find that 80% more people (i.e., $(27 - 15)/15 * 100\%$) rate high trust ("highly likely" versus. "least likely" categories) in the case of payment apps (P-bar in the figure). However, in the case of gaming apps (G-bar) and health apps (H-bar), only 36% and 9% more people rate high trust in friends' recommendations. On the other hand, more people rate less trust in friends recommendations about news apps (N-bar). Therefore, we conclude that people consider friends' recommendations with a high level of trust when choosing payment apps.

Next, we consider **family members** as a recommender group. In the figure, we observe that the number of people who mention high trust in choosing a payment app (P-bar) based on a family member's recommendation is 2.67 times (i.e., 32 versus 12) higher than the number of people who mention low trust. Similarly, compared to the number of people who mention high trust in a family member's recommendation while choosing news apps (N-bar) and health apps (H-bar) is 1.19 times (i.e., 31 versus 26) and 1.32 times (i.e., 29 versus 22) higher than the number of people who mention low trust. On the other hand, more people mention low trust in a family member's recommendation when choosing a gaming app (G-bar). Hence, we conclude that more people are highly likely to use a payment app when recommended by their family members, compared to any other recommender group.

Next, we analyze users trust in different types of app when they are recommended by **external recommenders**, such as healthcare providers or physicians, news channels, or advertisements. In the case of health apps (H-bar), the number of people who mention high trust is 2.85 times (i.e., 37 versus 13) higher than the number of people who mention low trust. Compared to health apps, more people mention low trust in the other three types of apps when referred by external recommenders, such as news channels (P-bar) or advertisements (N-bar and G-bar). Hence, we conclude that people are more likely to use a health app when it is recommended by a health expert, such as a physician or a healthcare provider.

Finally, we consider the **no recommendation** category. In Fig. 4, we observe that in general more people rated low trust while selecting all types of apps without any recommendation. Around 1.94–3.8 times people are likely to rate low trust compared to rating high trusts. Hence, we conclude that people need some guidance either from family/friends or external recommenders while selecting smartphone apps.

As we have found people mention high trust in payment (P) apps when they are recommended by **friends** and **family members**, and high trust in health (H) apps, when they are recommended by health experts, such as healthcare providers or physicians, therefore, we will next investigate significance of different features, such as marital status, educational background, gender, app development experience, and age in choosing a health (H) app (Sect. 3.1) or payment (P) app (Sect. 3.2) with high trust (4 or 5 ratings). Throughout this manuscript, p_i and $\hat{p}_i$ are used to indicate population and sample proportions of the i^{th} group.

3.1 Factors Affecting User-Trust in Health Apps

In this section, we analyze the statistical significance of various parameters, such as user trust, educational attainment, gender, app development experience, age, and marital status, when selecting a health app.

Significance of Gender. The percentage of men and women who have high trust in health applications that are suggested by healthcare professionals or doctors is compared using the $z-test$ to see if there is a statistically significant discrepancy between both, i.e., null hypothesis, $H_0 : p_1 = p_2$, where $\hat{p}_1 = \frac{16}{24}$ and $\hat{p}_2 = \frac{21}{36}$ are the fractions of male and female who provide a high rating when conveying their trust in health (H) apps recommended by physicians or healthcare providers. With $z = .6$ and $p = .533$, we are unable to reject the null hypothesis at the .05 level of significance. Thus, we draw the conclusion that trust in health (H) apps suggested by doctors or other healthcare professionals is not comparable for males and females.

Significance of Age. We conduct the χ^2 proportion test with the null hypothesis that "when it comes to user-trust in health apps recommended by healthcare providers or physicians, there is no statistically significant discrepancy among the fractions of individuals from different age groups" (i.e., $H_0 : p_1 = p_2 = p_3 = p_4 = p_5$, where $\hat{p}_1 = \frac{5}{9}$, $\hat{p}_2 = \frac{25}{37}$, $\hat{p}_3 = \frac{3}{5}$, $\hat{p}_4 = \frac{1}{4}$, and $\hat{p}_5 = \frac{3}{5}$ are the fractions of subjects from different age groups that provide a high rating in health app when recommended by physician or healthcare providers). At .05 level of significance, we cannot reject the null hypothesis with $\chi^2(4) = .8602$ and $p = .93$. Therefore, we draw the conclusion that user trust in health (H) apps suggested by doctors or other healthcare professionals does not significantly differ among the five age groups.

Significance of Educational Background. From our analysis, we dropped the subject who "passed high school" (Fig. 2) and does not have high trust in the health (H) apps when recommended by healthcare providers or physicians. We take into account the remaining three categories of people: those who completed senior high school, graduated, and obtained a master's degree. We use the χ^2 proportion test with the null hypothesis that "there is no statistically significant distinction among the fractions of individuals from different education backgrounds, in terms of user-trust in health apps when recommended by physicians or healthcare providers" to examine the significance among different groups. (i.e., $H_0 : p_1 = p_2 = p_3$, where $\hat{p}_1 = \frac{3}{9}$, $\hat{p}_2 = \frac{11}{20}$, and $\hat{p}_3 = \frac{23}{30}$ are the fractions of subjects from the three groups that provide a high rating in health app when recommended by physician or healthcare providers. With $\chi^2(2) = 1.5786$ and $p = .454$, we are unable to reject the null hypothesis at the .05 level of significance. Thus, we draw the conclusion that there is no discernible difference in user-trust in health (H) apps suggested by doctors or other healthcare professionals across the three groups of people.

Significance of App Development Experience. When recommended by healthcare professionals or doctors, one participant with "advanced" app development expertise (Fig. 3) did not place a high level of trust in the health (H) apps. The "advanced" app development expertise and that participant are thus excluded from this research. The remaining three categories of people—those with no experience, intermediate experience, and no experience—are taken into consideration.

With the χ^2 proportion test and the null hypothesis "there is no significant discrepancy among the fractions of individuals from different groups, in terms of user-trust in health apps when recommended by physicians or healthcare providers", we examine the significance among groups of people based on app development experience (i.e., $H_0 : p_1 = p_2 = p_3$, where $\hat{p}_1 = \frac{18}{27}$, $\hat{p}_2 = \frac{11}{14}$, and $\hat{p}_3 = \frac{8}{18}$ are the fractions of subjects from the three groups that provide a high rating in health app when recommended by physician or healthcare providers. With $\chi^2(2) = 1.0179$ and $p = .601$, we are unable to reject the null hypothesis at the .05 significance level. Thus, we draw the conclusion that there is no discernible difference in user-trust in health (H) apps suggested by doctors or other healthcare professionals across groups with different app development experiences.

Significance of Marital Status. The proportion of single and married people who have high trust in health applications that are suggested by healthcare professionals or physicians is compared using the $z-test$ to see if there is a statistically significant discrepancy, i.e., null hypothesis, $H_0 : p_1 = p_2$, where $\hat{p}_1 = \frac{2}{9}$ and $\hat{p}_2 = \frac{35}{51}$ are the fractions of married and unmarried who provide a high rating when conveying their trust in health apps (H) recommended by physicians or healthcare providers. With $z = 2.6$ and $p = .0091$, we reject the null hypothesis at the .05 level of significance. Thus, we draw the conclusion that, when advised by doctors or other healthcare professionals, health (H) applications are more trusted by unmarried people than by married people.

3.2 Factors Affecting User-Trust in Payment Apps

In this section, we evaluate the statistical importance of several variables, such as gender, age, educational attainment, expertise in app development, and marital status on user trust when selecting a payment app.

Significance of Gender. We utilize the $z-test$ to see if there is a statistically significant discrepancy between the percentage of males and females who have high trust in payment (P) apps that are recommended by family or friends, i.e., null hypothesis, $H_0 : p_1 = p_2$, where p_1 and p_2 are the fractions of male and female who provide a high rating when conveying their trust in payment apps recommended by family members or friends. In the case of family members, we find $\hat{p}_1 = \frac{15}{24}$ and $\hat{p}_2 = \frac{17}{36}$ with $z = 1.2$ and $p = .2385$. Therefore, we are unable to rule out the null hypothesis at the .05 level of significance. Similarly, in the case of friends, we are unable to rule out the null hypothesis with z = 1.2 and p = .2217. Therefore, we draw the conclusion that males and females do not have a comparable level of trust in payment (P) apps that have been suggested by family or friends.

Significance of Age. With the "there is no statistically significant variation among the fractions of people from different age groups, in terms of user-trust in payment applications when recommended by family members or friends" null hypothesis, we utilize the χ^2 proportion test to examine the significance among the different age groups (i.e., $H_0 : p_1 = p_2 = p_3 = p_4 = p_5$, where p_1, p_2, p_3, p_4, and p_5 are the fractions of subjects from the five age groups that provide a high rating in payment apps when recommended by family members or friends. In the case of family members, we find $\hat{p}_1 = \frac{6}{9}$, $\hat{p}_2 = \frac{17}{37}$, $\hat{p}_3 = \frac{4}{5}$, $\hat{p}_4 = \frac{3}{4}$, and $\hat{p}_5 = \frac{2}{5}$ with $\chi^2(4) = 1.1300$ and $p = .889$. Therefore, we are unable to rule out the null hypothesis at the .05 level of significance. Similarly, in the case of friends, we are unable to rule out the null hypothesis with z = 1.558 and p = .816. Therefore, we draw the conclusion that there is no discernible difference in terms of user-trust in payment (P) apps suggested by family or friends across the five age groups.

Significance of Educational Background. When recommended by family members, we dropped one subject, who "passed high school" (Fig. 2) and did not report a high level of trust in the payment (P) apps. We take into account the remaining three categories of people: those who completed senior high school, graduated, and obtained a master's degree. We use the χ^2 proportion test with the null hypothesis that "there is no significant distinction among the fractions of people from different educational backgrounds, in terms of user-trust in payment apps when recommended by family members or friends" to examine the significance among different groups (i.e., $H_0 : p_1 = p_2 = p_3$, where p_1, p_2, and p_3, are the fractions of people from the three groups that provide a high rating in payment apps when recommended by family members or friends. In the case of family members, we find $\hat{p}_1 = \frac{4}{9}$, $\hat{p}_2 = \frac{8}{20}$, $\hat{p}_3 = \frac{19}{30}$ with $\chi^2(2) = .9125$ and $p = .634$. Therefore, we are unable to rule out the null hypothesis at the .05 level of significance. Similarly, when considering friends, with $z = 3.9142$ and $p = .141$, we cannot reject the null hypothesis. Therefore, we draw the conclusion that there is no discernible difference in terms of user-trust in payment (P) apps suggested by family or friends across the three groups.

Significance of App Development Experience. In the case of recommendations from family or friends, we drop one subject with "advanced" app development experience (Fig. 3) that did not report high trust in the payment (P) apps. The remaining three categories of people-those with no experience, intermediate experience, and no experience - are taken into consideration. We use the χ^2 test with the null hypothesis "there is no statistically significant distinction among the fractions of individuals from different educational backgrounds, in terms of user-trust in payment apps when recommended by family members or friends" (i.e., $H_0 : p_1 = p_2 = p_3$, where p_1, p_2, and p_3 are the fractions of participants from the three groups that provide a high rating in payment apps when recommended by family members or friends. In the case of family members, we find $\hat{p}_1 = \frac{18}{27}$, $\hat{p}_2 = \frac{7}{14}$, and $\hat{p}_3 = \frac{7}{18}$ with $\chi^2(2) = 1.05524$ and $p = .59$. Therefore, we are unable to rule out the null hypothesis at the .05 level of significance. Similarly, in the case of friends, we are unable to rule out the null hypothesis with z = .6364 and p = .727. Therefore, we draw the conclusion that there is no discernible difference in terms of user-trust in payment (P) apps suggested by family or friends across the three groups of people.

Significance of Marital Status. To verify if there is a statistically significant difference in the fraction of married and unmarried people who reported high trust in payment apps that are suggested by family or friends, we perform a

$z - test$, i.e., null hypothesis, $H_0 : p_1 = p_2$, where p_1 and p_2 are the fractions of unmarried and married who provide a high rating when conveying their trust in payment (P) apps recommended by their family members or friends. In the case of family members, we find $\hat{p}_1 = \frac{5}{9}$ and $\hat{p}_2 = \frac{27}{51}$ with $z = .1$ and $p = .8854$. Therefore, we are unable to rule out the null hypothesis at the .05 level of significance. Similarly in the case of friends, where $z = .8$ and $p = .4363$, we cannot reject the null hypothesis. Thus, we draw the conclusion that there is no discernible difference between married and unmarried people in terms of user-trust in payment (P) apps that are suggested by family or friends.

4 Conclusions

To the best of our knowledge, this is the first work that conducts a thorough investigation of user trust in different types of smartphone applications and recommenders using graphical and statistical approaches. Among the four types of apps investigated in this work, we find that users have a high trust in health apps when they are recommended by healthcare providers or physicians. Similarly, we find that users have a high trust in payment apps when they are recommended by friends or family members. These groups of recommenders probably have a better understanding of the features that a specific app should have. Therefore, it will important to bring these specific groups of recommenders and their recommendations to gain higher user trust and higher app utility and adherence. Additionally, we do not observe any significant difference in user trust due to background variations, except the marital status while choosing health apps. Therefore, our findings are generic across users with different backgrounds.

5 Limitations and Future Work

This work has some limitations, which we plan to address in the future. First, the dataset used in this work is relatively small, i.e., consists of 60 smartphone users. However, we perform proportion analysis to determine the significance of user backgrounds. Therefore, findings from this work show some guidelines for future app developments. Also, some of the categories, e.g., high school in the educational background and advanced app developer, have low user count; therefore, we are not able to investigate their significance. Finally, to develop an app with high utility and adherence, it is important to understand various user concerns, including privacy and security, confidentiality, difficulty in-app usage, among many others as well as a user's choice to configure an app and its features in addition to user trust in different types of recommenders. In the future, we will further investigate user concerns and their choices to configure apps.

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