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Analyzing mobile app data demand and usage behavior in Sri Lanka

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Abstract

Owing to the rapid advancement of mobile computing, daily human practices have become more efficient and convenient. Consequently, the number of mobile app users has increased drastically over the last ten years, and a significant amount of energy is consumed by those mobile apps where the energy consumption depends on the data usage of the apps. Therefore, it is important to optimize data consumption to ensure sustainable digitalization. Mobile app personalization is one of the vital areas to optimize the data consumption of mobile apps. In this research, mobile app data usage and user experience data were collected and analyzed quantitatively and qualitatively. The data were collected from 40 Android smartphone users in Sri Lanka. Primarily, semi-structured interviews were conducted to collect qualitative data to identify mobile app usage patterns. In addition, data usage of each mobile app was collected using the in-built data usage tracker in Android smartphones for four months. Descriptive and correlation analyses were used to analyze quantitative data, whereas thematic and content analyses drew insights from the collected qualitative data. Our findings show the most data-demanding mobile app categories in terms of data consumption as social media, video players & editors, and communication. Moreover, users aged between 21 to 30 contribute to the high data consumption in mobile app usage. In addition, qualitative analysis shows that app usage behavior varied during and after the pandemic, and elderly (51-65 years) mobile app users use only a limited number of features from an app.

Keywords: Mobile app usage, Data demand, App personalization, User experience, Sri Lanka

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Introduction

In the modern world, convenient digital devices, smartphones have become an indispensable part of everyday life, outweighing computers. With the rapid advancement of technology and the complexity of human needs, people have established and maintained their daily routines through various mobile apps available in the mobile app market. According to the report from Statista, yearly mobile app downloads worldwide have increased by more than 80% from 2016 to 2022 (Ceci, 2022a). Therefore, understanding mobile app usage behaviors is crucial for various stakeholders, including app designers, developers, service providers, and users (Li et al., 2022; Huang et al., 2017). Nevertheless, the data consumption of mobile apps has been poorly investigated and understood in relation to mobile app personalization. Therefore, it is necessary to investigate comprehensively to understand insights into mobile app data consumption and app usage patterns. For example, the mobile application's user interface (UI) design is a key factor that determines the app's data consumption. While sustainable interaction design methods have focused on sustainable human-computer interaction research, there is a gap in quantifying and analyzing existing mobile app usage patterns (Nyström & Mustaquim, 2018).

Mainly, there are three domains in mobile app usage analysis; (1) App domain (2) User domain (3) Smartphone domain (Li et al., 2022). The present research aims to address the app domain and user domain by discovering mobile app usage patterns of different user groups. Moreover, mobile app data demand depends on numerous factors. For example, it depends on user-related factors such as mobile app usage patterns and other factors, namely the size of the mobile application, services provided by the application, etc. Among them, mobile app usage behaviour is key to data demand. Previous researchers have focused on analyzing data demand for different app categories in different countries (Lord et al., 2015; Singh et al., 2017; Widdicks et al., 2017). Yet, the applicability of the previous findings to describe the present usage patterns is questionable because of the rapid advancement of mobile technology and changes in human lives. Furthermore, country-wise differences exist in mobile app usage behaviours (Lim et al., 2015). To the best of our knowledge, no research has been conducted to study data demand in mobile app usage behaviour within Sri Lanka in the recent past. Consequently, studying the present data demand of diverse mobile applications within Sri Lanka is crucial to gaining insights into current usage patterns.

Moreover, it is a common fact that mobile apps are designed for the broadest audience and expect to work well with all users (Zhao et al., 2016). This may indirectly consume more data and energy. For example, a heavy mobile app may have a diverse range of functionalities, but one may never use at least half of them. These applications can be redesigned in a better way to save data and use it effectively for specific user groups. Even though thousands of mobile apps are available, true standards for mobile UI design patterns do not exist (Punchoojit & Hongwarittorrn, 2017). In addition, usability evaluation is a confusing task as it needs to cover the quality of the app while catering to the user's emotions and beliefs (Weichbroth, 2020). According to the reasons mentioned above, studying mobile application usage patterns and scenarios is vital for introducing novel paradigms to reduce the data demand of mobile applications. Accordingly, two research gaps have been identified: the absence of current studies on mobile app data demand in Sri Lanka and the necessity for app personalization to optimize data usage. By addressing these gaps, this study aims to explore current mobile app data demand and usage behavior in Sri Lanka and investigate opportunities for app personalisation to reduce data consumption. Therefore, this research investigates how everyday practices have been established and maintained through mobile applications while quantifying modern current data consumption patterns of mobile applications based on different user groups. Based on existing literature, the research objectives are formulated as follows: firstly, to identify mobile user groups that significantly contribute to higher data demand. Secondly, to determine the app categories that can be personalized to mitigate this data demand. Small-scale reductions in energy consumption and minor adjustments to how individuals achieve their objectives can collectively contribute to sustaining society (Knowles et al., 2018). This supports the significance of our research objectives in identifying opportunities for personalized interventions to reduce data demand in mobile app usage, as even minor optimizations can have a meaningful impact on overall societal sustainability. Thus, the results of this analysis would help to introduce novel approaches to optimize the data demand in mobile application usage.

Materials and Methods

This research is primarily focused on the user domain and app domain. Further explained, the aim is to find the link between user characteristics and app usage data consumption by studying the regularities in usage behavior. The data and methodology used for this research are described in the following paragraphs.

Data Collection

The study was focused on Android smartphone users within Sri Lanka to collect quantitative and qualitative data on smartphone usage. Focusing on Android users is justified due to overwhelming prevalence in Sri Lanka (Sri Lanka: Monthly Mobile OS Market Share 2024). As of March 2024, Android held an 87.12% market share compared to iOS's 12.53%, ensuring the research captures the behavior of many smartphone users. This dominance allows for a representative sample that reflects the broader demographic. Additionally, Android devices are accessible across various socioeconomic groups, enhancing inclusivity. The built-in tools in Android devices facilitate easier data collection, aligning with the practical needs of the study. Furthermore, stratified random sampling by age ensures balanced representation, enhancing the robustness and generalizability of the findings. Previous similar studies have used fewer participants to collect qualitative data; for example, (Lord et al., 2015; Widdicks et al., 2017) each used less than 20 participants. To collect enough data, the number of participants was decided as 40. The study participants were recruited to participate in this study voluntarily, without any incentives for participation. Written informed consent was obtained prior to conducting the interviews and collecting the data. The sample size was determined to enhance the depth and breadth of the insights obtained to ensure robust and reliable findings. Mobile app usage behavior has been found to be significantly influenced by the age of the users (Andone et al., 2016; Arambepola & Munasinghe, 2020). Therefore, stratified random sampling was used, considering age as the stratification variable for selecting participants. Participants aged between 20 and 65 were categorized into four groups (ages 21-30, 31-40, 41-50, and 51-65). This approach ensures balanced representation across different age demographics, allowing the study to identify and analyze age-specific patterns in mobile app usage behavior. Representatives from each group were selected through social media and in-person contacts. Data on mobile app usage in Android smartphones was collected using the built-in tool that provides monthly mobile data usage and Wi-Fi usage data. Data consumption was collected for four consecutive months. The dataset includes the monthly data consumption of each mobile app used by the participant, encompassing both foreground data (data used by the user) and background data (data used by the app without user interaction or visibility, such as data syncing and downloading updates). All data were collected and stored anonymously using a code.

It is not possible to link mobile apps to specific practices, so interviews were necessary to discover how mobile apps were used in different situations in everyday life (Lord et al., 2015). Therefore, semi-structured interviews accompanied the app usage data consumption by collecting qualitative data regarding app usage behavior. Interviews were conducted physically and lasted 45-60 minutes. Twenty-three questions related to mobile app usage were covered in the interviews and divided into three sections. Section I included participants' information, such as user demographics for user profiling, age, gender, education level, occupation, etc. Section II included questions related to the user experience of smartphone and mobile app usage. Section III included questions related to mobile app usage behaviour and app usage frequency.

Methodology and Analytical Approach

This research employed a combination of quantitative and qualitative data analysis techniques to achieve comprehensive insights. Quantitative data analysis techniques were utilised to analyze mobile app data consumption. Descriptive statistics were used to depict the fundamental characteristics of the dataset. At the same time, correlation analysis was employed to determine the strength and direction of relationships between variables (user groups and app categories).

Qualitative data analysis techniques were employed to analyze interview transcripts and survey data. Among the qualitative techniques, content analysis was utilized to quantify qualitative data, while thematic analysis was applied to uncover underlying patterns. The researcher transcribed each interview, aligning with the prepared questions, and subsequently re-coded for various themes. Furthermore, mobile apps and data usage were manually categorized according to the Statista mobile app categorization in 2022 (L. Ceci, 2022b). Furthermore, descriptive statistical analysis was used to determine the dominant mobile app categories in terms of data consumption and describe the demographic factors of the participants.

Results and Discussion

Descriptive statistical analysis was performed to summarize and demonstrate the demography of the study participants. Stratified random sampling was utilized, considering age as the strata variable, and an equal number of smartphone users were selected from each age group (Ages 21-30, 31-40, 41-50, and 51-65). Among the participants, 42.5% represent males, and 57.5% represent female participants. However, there are some dominant user groups in education level and employment status, as shown in Figures 1 and 2. For example, the majority (72.5%) of participants were full-time employees.

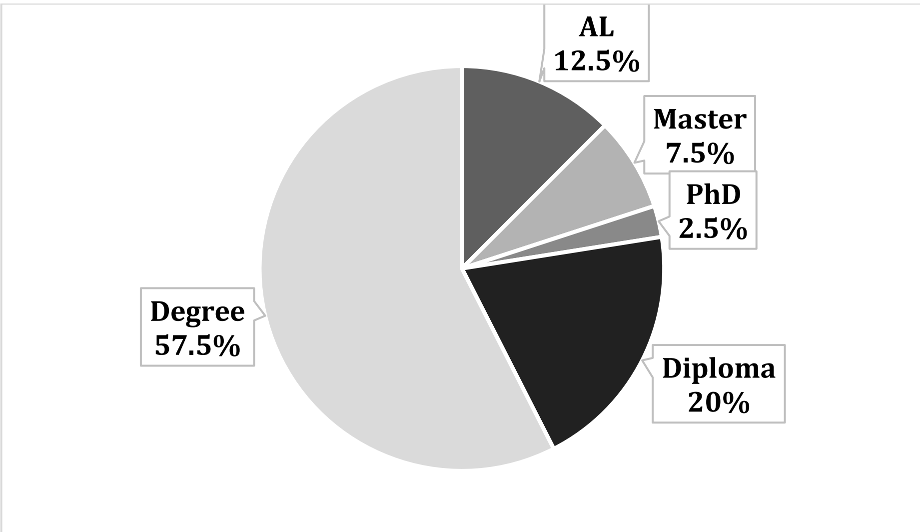

Figure 1: Education level of participants

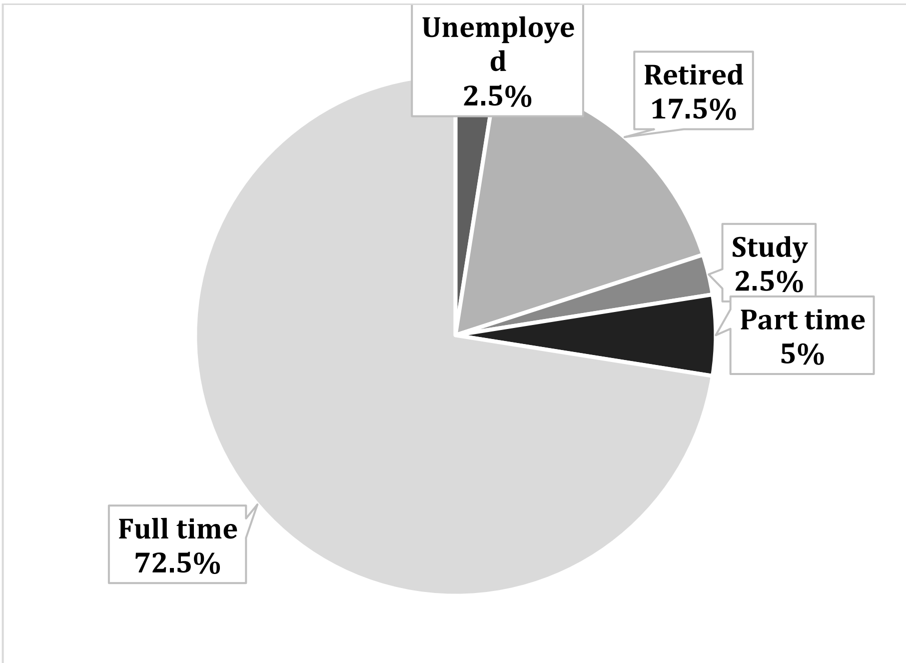

Figure 2: Employment status of participants

Everyday data consumption practices

Qualitative data analysis was carried out to understand how mobile apps established and maintained everyday practices. Informal interviews were conducted using a pre-prepared semi-structured questionnaire, asking open-ended cross-questions for more insights. Questions were prepared based on the mobile app-related background questions, such as frequency of mobile app downloads and reasons, and the second set of questions was based on usage of mobile app categories. Before starting the mobile app-related section of the questionnaire, participants were asked to rate the frequency of use of each mobile app category. The rest of the questions were asked based on the ratings provided. None of the participants used news and magazine apps and dating apps, while all the participants (100%) used communication apps. Therefore, communication is the most widely used mobile app category. Previous studies have also claimed the same conclusion (Singh et al., 2017; Widdicks et al., 2017).

According to the content analysis, every participant (100%) stated that their mobile app usage behaviour (both practices and frequency) changed during the last two years, especially due to the COVID-19 pandemic. Among them, 92.5% of participants stated that it was a positive change, while the rest stated that it was a negative change for them. The reasons they mentioned for the positive change are summarized and shown in Table 1 according to age groups. On the other hand, the remaining participants (7.5%) mentioned that the negative side of change in behaviour is the addiction to social media apps after using those apps for long hours (3-6 hours per day). However, mobile apps that belong to the categories that surround daily routines, namely shopping, education, business and work, finance, and food and drink, have become more popular during the COVID-19 pandemic period as they established their tasks with such applications. Furthermore, they are still maintaining the same practices continuously.

Table 1: Reasons for positive change in using mobile apps: Opinions of the users.

Age group	**Opinions of the users/ Comments**
21-30	Get to know new features in apps
	Get to know new apps for spending leisure time in a productive way (eg: Gamification based productive apps)
	Save travel time
31-40	Get to know new apps (eg: parenting apps, finance apps)
	Save travel time
51-65	Learn new features of apps and was able to explore new things through mobile apps (eg: Video players)

App usage behaviour towards app personalization

Thematic analysis related to sustainable app usage behavior and user experience was conducted under four themes: "app features," "lightweight mobile apps," "app updates," and "app redesigning." It was found that every participant had never used certain features, with 07 elderly users (aged 51-65) unaware of the existence of some features, such as enabling and disabling the auto-play feature in video players. Only 03 participants (7.5%) were using lightweight mobile apps for some categories, such as social media. Although 13 participants were aware of lightweight apps, they were unaware of their pros and cons. Users aged 51 to 65 either used automatic app updates or never explicitly updated an app via the app market. Finally, every participant showed their interest in using the re-design apps if it can reduce data consumption while providing the same features they currently use. This is a vital opportunity to promote lightweight mobile apps for specific mobile app categories which consume a higher amount of data. Moreover, these findings can be used as an initiative for mobile app feature personalization based on the age group.

Analysis of data demand

Second, the data demand from the collected dataset was quantified. The mean value of 04 months of data consumption was used to calculate the average data consumption of each participant. Missing values were imputed with the mean during the data cleaning stage. Social media, video players and editors, and communications were identified as the most demanding mobile app categories in terms of data consumption, and those contributed 44%, 33%, and 20% for the total data consumption, respectively. This complies with the result of a similar analysis conducted in 2017 (Widdicks et al., 2017). They have identified mobile app categories watching, social networking, communication and online dating as the most demanding in 2017. Even though app categories business and work, and education are used frequently, those apps were identified as low data-consuming app categories (eg: approximately 1% according to this analysis). Moreover, users aged between 21 and 30 contribute to the high data demand as shown in Figure 3.

In addition, results revealed that young mobile app users (age 21-30) consume more data than the elderly (51-65), with a moderate negative relationship between age and total data consumption (Pearson correlation coefficient value is -0.61). More specifically, Table 2 shows the correlation between the user's age and data consumption of each mobile app category. It clearly shows that data consumption has decreased with age in all the considered mobile app categories in this research except music and audio apps. Nevertheless, gender does not show any notable relationship with data consumption of 15 app categories. However, the Pearson correlation shows moderate relationships with mobile app categories maps, books & references, and finance apps, respectively, with correlation coefficient values of 0.488, -0.351, and 0.372. This implies that female users tend to use (consume more data) books and reference apps more than male users. Also, male users consume more data on maps and finance apps.

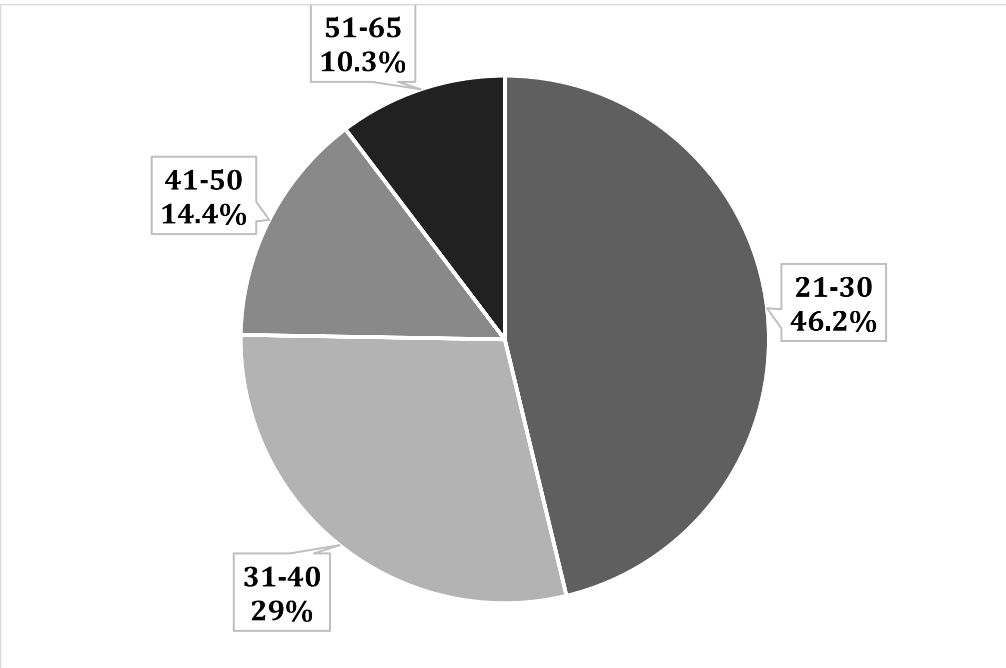

Figure 3: Total mobile app data demand by age

Table 2: Correlation between the age of the users and data consumption of each mobile app category

	Mobile app category	Pearson correlation coefficient
Age	Social media	-0.630
	Communication	-0.465
	Entertainment	-0.233
	Video players and editors	-0.213
	Games	-0.158
	Education	-0.108
	Business and work	-0.196
	Music and audio	0.0318
	Food and drink	-0.172
	Shopping	-0.196
	Maps	-0.333
	Productivity	-0.359
	Travel	-0.248
	Books and reference	-0.261
	Sports	-0.185

Further examination was conducted on how each age group contributed to the data consumption of identified the most demanding app categories. The scatter plot shown in Figure 4 illustrates how data demand has been distributed among different age groups. It clearly shows that the age of around 30 has contributed to high data consumption using the most data-demanding app categories.

Both qualitative and quantitative analysis identify opportunities to introduce lightweight mobile apps to save data. For example, existing lightweight mobile apps provide clear evidence of where data is saved. The regular Facebook app occupies 205 MB of storage on an Android smartphone, while Facebook Lite only occupies 5.57 MB (Khemch & Ani, 2023). This represents a substantial reduction (over 95%) in data consumption, as app size significantly impacts data usage. The analysis shows that elderly users (aged 51-65) contribute to higher data wastage by using regular apps without utilizing most of their features, which indirectly wastes energy. Therefore, introducing lightweight versions of mobile apps, personalizing apps for the most demanding categories based on user groups, and increasing awareness can promote sustainable data-saving practices. This approach optimizes mobile app data consumption through targeted app personalization, leading to a more efficient and user-friendly experience.

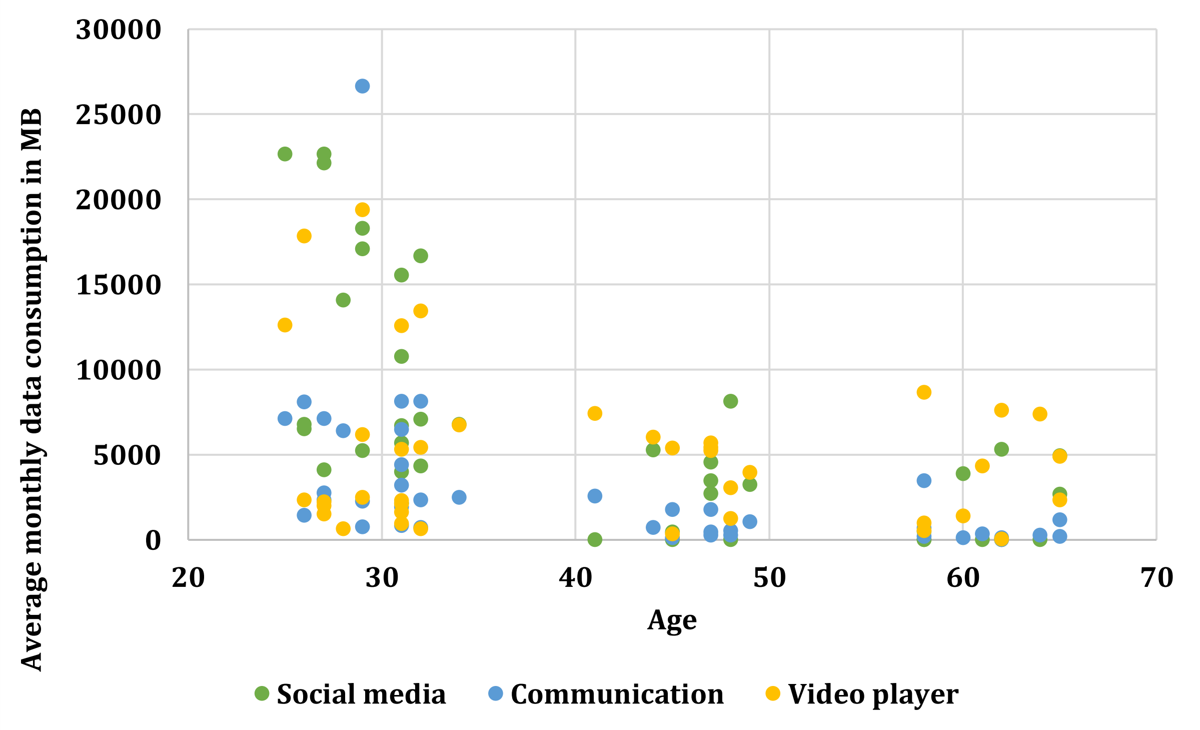

Figure 4: Average monthly data consumption for dominant app categories by age

However, there were some challenges when categorizing mobile apps as one app may fall into multiple categories in some scenarios. For example, some participants used the Zoom app for the purpose of education while some used it for work and business. Moreover, some apps belong to multiple categories by default such as Pinterest. Besides, some local apps such as MyLeco were difficult to categorize.

Limitations and Future Works

It is important to point out certain limitations in this research work. Even though the sample size (40 Android smartphone users) is sufficient for the quantitative and qualitative in-depth analysis to gather mobile app user behaviour when compared to the previous similar studies (Widdicks et al., 2017; Lord et al., 2015), the results would provide more generalized insights if the sample size was increased. However, a stratified random sampling method was used here to represent each user group in the considered strata age when collecting the small-scale dataset.

As for future works, this research will be extended in three directions as follows. (1) Collecting a large-scale dataset for quantitative analysis and comparing it with the current results. For example, occupation can be a significant factor in mobile app data consumption, but it was not focused on at this stage and will need to be considered in future analysis with the large-scale dataset. (2) Analyzing mobile app user reviews to extract more insight based on the user experience of the existing mobile apps. (3) Proposing a framework that consists of mobile app design guidelines to reduce the high data consumption through data demand. For example, identifying notable apps which can be redesigned as personalized lightweight versions for the different user groups and including feature customization options.

Conclusion

The most demanding mobile app categories in Sri Lanka in terms of data consumption were identified as social media, video players & editors, and communication. In addition, it was identified that users aged between 21 to 30 contribute to the high data consumption in mobile app usage in Sri Lanka. Furthermore, there is a moderately negative relationship between the users' age and the total mobile app data consumption. The output of the analysis is useful for mobile app designers to enhance the user experience of mobile apps through app personalization while providing data-saving features for specific mobile app categories.

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