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Constructing Data-Driven Personas through an Analysis of Mobile Application Store Data

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Abstract: As smartphone segments have become more complex in recent times, the importance of personas for designing and marketing has increased. Earlier, designers focused on traditional qualitative personas but have been criticised for the lack of evidence and outdated results. However, although several methods of quantitative persona creation have been developed over the last few years, the use of mobile application store data has not yet been studied. In this research, we propose a framework using work domain analysis to help designers and marketers to build personas easily from mobile phone application store data. We considered the top 100 applications, which were ranked based on the number of devices using each application, how often each application was used, and the usage time. After proposing a new framework, we analysed data from a mobile application store in January and August 2020. We then created quantitative personas based on the data and discussed with experts whether the created personas successfully reflected real changes in mobile application trends.

Keywords: personas; HCI; data-driven UX; quantitative persona; mobile phone application store

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1. Introduction

As smartphone segments have become more complex in recent times, the importance of personas is increasing [1–5]. Smartphones are increasingly ubiquitous, and many users use multiple mobile devices to accommodate work, personal and geographic mobility needs [6,7]. The term "personas" was first introduced by Cooper [8] to depict a new way of generating user profiles. Cooper stated, "personas are not real people . . . they are hypothetical archetypes of actual users . . . defined with significant rigor and precision" [9]. In other words, personas are regarded as imaginary people constructed to stand in as concrete target users for products [10–13]. Personas are essential for the user-centred design process [10,14–16], as they describe representations of segments of actual users presented as a single imaginary person [13,17]. Pruitt and Grudin suggested that personas serve as a conduit for including a broad range of qualitative and quantitative data and concentrate on aspects of design and usage that other methods do not [2,18]. In general, the artefact is a persona description implying attributes of the user segment that the fictionalised person represents [17,19]. In order to comprehend a user's workflow by scrutinising that user's behaviour, goals, needs, wants and frustrations [20], personas are an important starting point to design the product, system and service. Traditionally, personas could be built based on insights from user research. The designer carefully considered market insights and the concept of the product to be developed; then, they created an image representative of the users.

Although personas are important for designing and marketing to target users, persona generation faces some issues because it still relies on traditional qualitative methods. Even though the traditional method of building personas has been widely and popularly used for a long time, there are several concerns.

First, generating personas is an expensive, difficult and slow process [17,20,21]. Second, the generated personas can quickly become outmoded [17,21,22]. Finally, generating a persona through the traditional method is not based on first-hand customer data, and if it is based on first-hand customer data, the dataset is not of a sample size that can be considered statistically significant [2,23,24].

However, UX designers and marketers on mobile phones still use traditional methods such as surveys, interviews or user observations. There are several reasons for this. First, there is no basic framework to create a quantitative persona based on mobile phone usage. Second, it is not easy to identify and extract valuable data from mobile usage data. Third, designers and marketers experience difficulty in gleaning insights from vast amounts of data.

Although a mobile phone is a widely used device these days, and user trends are changing fast, methods of creating quantitative personas based on mobile phone data have not yet been developed. To overcome the above issues, some researchers have attempted to develop personas based on user data [17,20,25,26]. However, there are various types of user data. Zhang, Brown and Shankar used data about clicks on websites to analyse user behaviours and proposed a framework for creating personas [25]. Jung et al. reported that they developed a methodology for persona generation using real-time social media data [17]. However, these data-based methods cannot cover all aspects of mobile phone usage. Zhang, Brown and Shankar describe personas belonging to the PC environment rather than relating to mobile phone usage, while Jung et al.'s research is more relevant to social media usage [25].

Although there is research into using data to create quantitative personas, there is no research into providing a method of creating personas based on all data related to mobile phone usage. For designing mobile phones, personas representing the characteristics of mobile phone usage are important because of the increasing tendency to develop various distinct segments and models of mobile phones. Thus, in order to define a target user for each mobile phone segment, it is necessary to analyse mobile phone usage and then generate personas that each represent a specific segment of mobile phone users. To build personas easily based on mobile phone usage, we hypothesised that we could generate personas based on various data from the mobile application store because application store data can indicate mobile phone usage trends and is sensitive to changes in the mobile phone user's lifestyle. For example, if the use of the "Walmart Shopping & Grocery" application had increased in August 2020 compared with January 2020, we could assume that the trend of mobile phone usage has changed towards online shopping. This also induces the change of user personas towards shopping.

In this research, we propose a framework by applying work domain analysis (WDA) to help designers and marketers create quantitative personas easily from mobile phone data, especially mobile application store data. We bought various mobile store ranking data from a mobile application store data agency. The system provides a list of the top 100 applications. The ranking is based on the number of devices that used each application, the number of times each application was used per device and the length of time for which the application was used. Using these data, we initially propose a framework to extract insights to generate personas with respect to mobile phone usage. Then, we provide an example of quantitative personas created by the framework. We also discuss its usefulness with experts. Finally, we validate the resultant personas through expert interviews.

2. Related Works

Salminen et al. suggested that quantitative persona creation has immense potential, as it assists UX-related designers to obtain insights [22]. Quantitative user persona creation uses user data that can be analysed from online analytics and digital media platforms to better and deeply comprehend their users and customers [22,26]. Zhang, Brown and Shankar insisted that the traditional data collection methods to create personas, such as surveys, self-reports, interviews and user observations, have limitations because these data are not a direct reflection of user behaviours [25]. In addition, those data collection methods are weak at reflecting actual workflows, expensive and easily outdated when a persona's workflow is changed [21,23]. To overcome these issues, Zhang, Brown and Shankar proposed a quantitative bottom-up data-driven approach to create personas [25]. To create personas using quantitative data, they collected user behaviour via clicks from telemetry data. Then, they combined 3.5 million clicks from 2400 users into 39,000 clickstreams and organised 10 workflows via hierarchical clustering [25]. Using a statistical method, they generated five representative personas [25]. In order to validate the personas created, they used an expert interview with user behaviour experts to check whether the workflows and the goals of the personas represented actual product use [25].

A related study was conducted by Jung et al. [17]. They used social media data to propose a new methodology for persona generation [17]. They collected a large volume of social media accounts involving more than 30 million interactions from users from 181 countries engaging with more than 4200 digital products [17]. To create personas, they demonstrated a new methodology to identify user segments and then created persona descriptions [17].

Each of these two works used a different idea and data to create personas because personas should represent a selected domain or theme and so they can be different. We found a research gap: there is no research regarding generating personas using mobile phone application store data even though mobile applications require the development of personas most urgently. In addition, to use the mobile application store data, a framework must be built to analyse the data. In the next section, we propose a new framework by using WDA to demonstrate how to use various data from the mobile application store.

3. A New Framework to Use Mobile Application Store Data

In this section, we propose the new framework using work domain analysis. WDA is a useful framework to identify and represent the functional properties of a work system [27–29]. It supports the identification of functional properties at multiple levels of abstraction and expresses them in a means–end hierarchy to present the relationships between functions at various levels of abstraction [27–29]. Cognitive work analysis and the contribution of work domain analysis to it are described fully by Vicente [30]. To create personas based on various data from a mobile application store, we conducted a focus group discussion (FGD) with four experts. This FGD helped to determine which data from the mobile application store can be useful to create personas [31,32].

The results of the WDA created based on the FGD are shown in Figure 1. The functional purpose generally refers to the "designed-for purpose" of the work domain [33]. The ultimate goal of the framework is to create personas using data from an application store. At the abstraction purpose level, the framework should help to represent user characteristics determined based on the data analysis. The generalised function depicts that data analysis statistically. It requires analysing the demographic information, device information and ranking change. Those components influence the user characteristics. Physical function describes the demographic information, device information, the number of devices that used each application, the number of times each application was used and the usage time of the application involved to aid in finding out the attributes of usage from the mobile application store. The number of devices using the app refers to the number of devices that used a specific application in a specific period. The number of times the application was used denotes the number of times the specific application was used on the sample devices. The usage time of the application depicts the time duration of using the specific application on the sample devices. At the physical form level, age, gender, region, mobile device version, OS version, application name and application category are distributed from the data collection system. They are regarded as the fundamental application store data and are chosen from the data collection system.

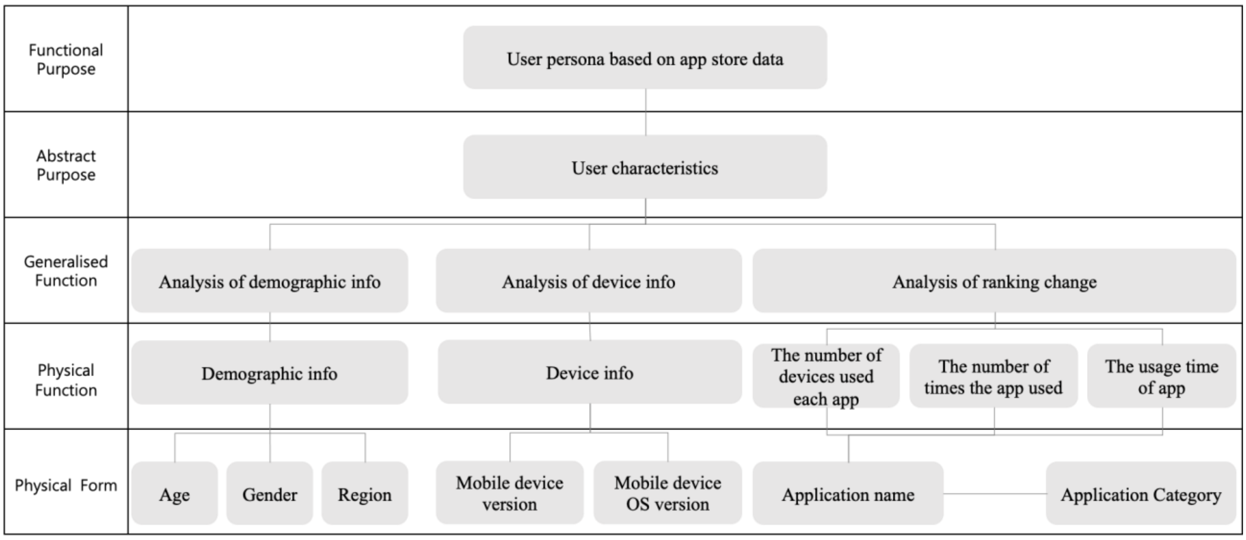


Figure 1. WDA of the new framework for creating personas based on the application store data.

4. Quantitative Personas Creation from the Framework

Through the system, we collected a variety of data from the application store related to 1,617,430 sample devices in January and August 2020 to identify the changes in personas influenced by the COVID-19 pandemic. The area was the United States, and the age group was all ages. We purchased only Android phone usage data at this time, owing to limited resources. In addition, although we added demographic data in the WDA, our purchased data did not include age, gender and region-related data. We will discuss this further in the discussion section.

The process for creating a persona is as follows (Figure 2). First, we collect various data that are described at the physical form in the WDA (Figure 1). We collected a list of 100 applications ranked based on three basic data: the number of devices that used the application, the number of times the application is used per device and the usage time of the application. Second, in order to calculate the ranking, the weighting values were distributed differently to each data, depending on their importance. Some apps were installed by many users, but the actual usage time was small. By contrast, some apps were installed by a small number of users, but the actual usage time was high. For example, the Uber driver application was used on a few devices but used for a long time. Therefore, the Uber driver cannot be considered a representative application to identify user characteristics. In addition, setting applications are installed on all devices but used for a short time.

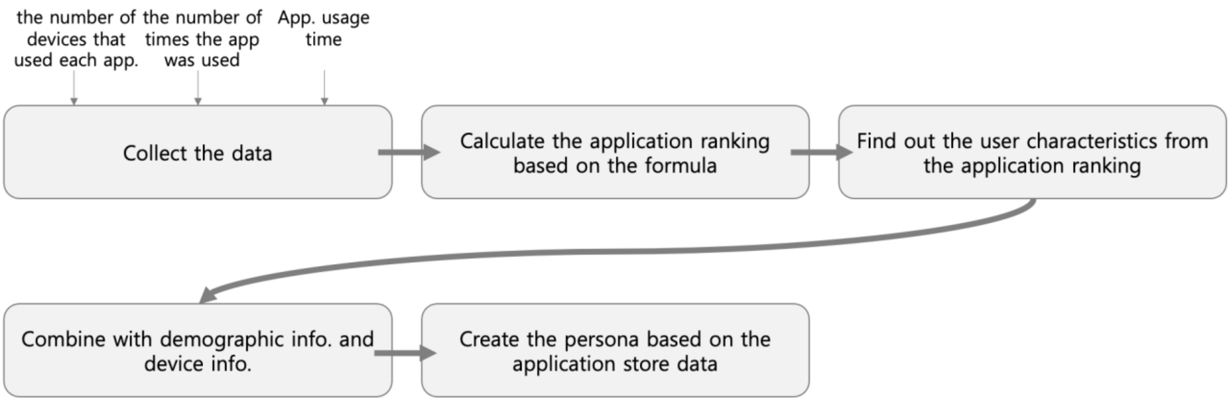


Figure 2. Process of creating a persona.

Hence, to determine the n top-ranked applications, we assigned different weights according to the importance of the data. The weighting was distributed as follows: the number of devices that used each application was assigned a weight of 20%, the number of times each application is used per device was assigned a weight of 50% and application usage time was assigned a weight of 30% (Figure 3). We regarded that an increase in the number of devices installing a specific application is most reflective of a lifestyle change of users. The next priority is the number of uses per device and then the time duration of application usage.

Top n ranking application list = 0.2 × the number of devices that used each application + 0.5 × the number of times each application is used per device + 0.3 × application usage time

Figure 3. Method to determine the top-n applications.

After these calculations, we generated the top 100 application rankings by applying the above calculation (Table 1). Table 1 presents the top 100 applications ranked over two different periods, namely, January 2020 and August 2020. Next, we categorised each application into the representative category. In Figure 4, the tree maps indicate the changes in application trends between January (a) and August (b). Thus, the changing trends can be easily compared between two different periods. Then, we counted and compared the number of each category (Figure 5). Specifically, we considered the change in application usage trends through the tree map, graph (Figures 4 and 5) and Table 1. Finally, we created four different types of personas based on the list (Figure 6). At this stage, as we mentioned earlier, we could not collect demographic information in the data. Therefore, the demographical setup was designed artificially.

Table 1. Top 100 applications in January and August 2020.

	January	August
1	Facebook	Facebook
2	YouTube	YouTube
3	Google Chrome: Fast & Secure	Google Chrome: Fast & Secure
4	Instagram	Instagram
5	Samsung Messages	Samsung Messages
6	Samsung Call	Samsung Call
7	WhatsApp Messenger	TikTok—Trends Start Here
8	Snapchat	WhatsApp Messenger
9	TikTok—Trends Start Here	Snapchat
10	Netflix	Verizon Messages
11	Verizon Messages	Netflix
12	Samsung Internet Browser	Samsung Internet Browser
13	Twitter	Messenger—Text and Video Chat for Free
14	Maps—Navigate & Explore	Maps—Navigate & Explore
15	Messenger—Text and Video Chat for Free	Twitter
16	Reddit	Pokémon GO
17	Hulu: Stream TV shows and watch the latest movies	Google
18	Google	Discord—Talk, Video Chat & Hang Out with Friends

Table 1. *Cont.*

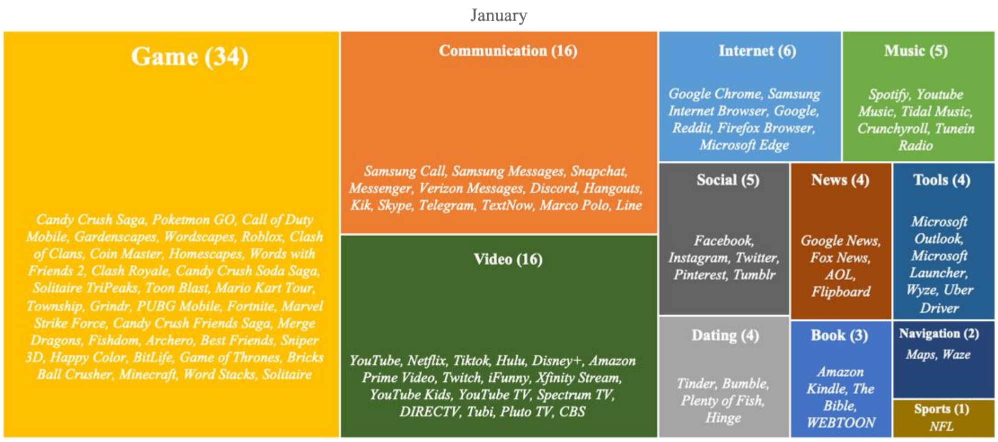
	January	August
19	Spotify: Listen to new music, podcasts, and songs	Reddit
20	Waze—GPS, Maps, Traffic Alerts & Live Navigation	Spotify: Listen to new music, podcasts, and songs
21	Pokémon GO	YouTube Music—Stream Songs & Music Videos
22	Messages	Hulu: Stream TV shows and watch the latest movies
23	Discord—Talk, Video Chat & Hang Out with Friends	Messages
24	Candy Crush Saga	Waze—GPS, Maps, Traffic Alerts & Live Navigation
25	YouTube Music—Stream Songs & Music Videos	Twitch: Livestream Multiplayer Games & Esports
26	Pinterest	Microsoft Outlook: Organize Your Email & Calendar
27	Microsoft Outlook: Organize Your Email & Calendar	Yahoo Mail—Organized Email
28	Amazon Kindle	Amazon Kindle
29	Disney+	Roblox
30	Tinder—Dating, Make Friends and Meet New People	Candy Crush Saga
31	Call of Duty®: Mobile	Tinder—Dating, Make Friends and Meet New People
32	Uber Driver	News Break: Local Breaking Stories & US Headlines
33	Amazon Prime Video	Amazon Prime Video
34	iFunny—fresh memes, gifs and videos	ZOOM Cloud Meetings
35	Clash of Clans	iFunny—fresh memes, gifs and videos
36	Twitch: Livestream Multiplayer Games & Esports	Robinhood—Investment & Trading, Commission-free
37	Kik	Hangouts
38	Hangouts	Firefox Browser: fast, private & safe web browser
39	Words With Friends 2—Free Multiplayer Word Games	SmartNews: Local Breaking News
40	Firefox Browser: fast, private & safe web browser	Call of Duty®: Mobile
41	Clash Royale	Kik
42	Homescapes	Roku
43	Gardenscapes	Microsoft Teams
44	Wordscapes	Disney+
45	Microsoft Launcher	Clash of Clans
46	Grindr—Gay chat	Words With Friends 2—Free Multiplayer Word Games

Table 1. *Cont.*

	January	August
47	Roblox	Wordscapes
48	Toon Blast	Coin Master
49	Tumblr	DoorDash—Driver
50	Bumble—Dating. Friends. Business	Uber Driver
51	Candy Crush Soda Saga	Toon Blast
52	Coin Master	Homescapes
53	Plenty of Fish Free Dating App	Google News—Top world & local news headlines
54	Google News—Top world & local news headlines	Tumblr
55	Township	Bumble—Dating. Friends. Business
56	Telegram	Happy Color™—Color by Number
57	The Bible App Free + Audio, Offline, Daily Study	Clash Royale
58	NFL	Gardenscapes
59	YouTube Kids	YouTube Kids
60	Solitaire TriPeaks: Play Free Solitaire Card Games	Candy Crush Soda Saga
61	LINE: Free Calls & Messages	Plenty of Fish Free Dating App
62	Fox News: Breaking News, Live Video & News Alerts	Fox News: Breaking News, Live Video & News Alerts
63	Skype—free IM & video calls	Fortnite
64	Viber Messenger—Messages, Group Chats & Calls	DuckDuckGo Privacy Browser
65	TextNow: Free Texting & Calling App	HBO Max: Stream HBO, TV, Movies & More
66	PUBG MOBILE—NEW ERA	Skype—free IM & video calls
67	Xfinity Stream	Viber Messenger—Messages, Group Chats & Calls
68	8 Ball Pool	Marco Polo—Stay In Touch
69	Merge Dragons!	WEBTOON
70	TIDAL Music—Hifi Songs, Playlists, & Videos	AOL—News, Mail & Video
71	WEBTOON	Telegram
72	MARVEL Strike Force—Squad RPG	TIDAL Music—Hifi Songs, Playlists, & Videos
73	Candy Crush Friends Saga	Fishdom
74	AOL—News, Mail & Video	Scrabble® GO—New Word Game
75	YouTube TV—Watch & Record Live TV	Microsoft Edge
76	Marco Polo—Stay In Touch	Xfinity Stream
77	Mario Kart Tour	Toy Blast
78	Flipboard—Latest News, Top Stories & Lifestyle	Hinge—Dating & Relationships

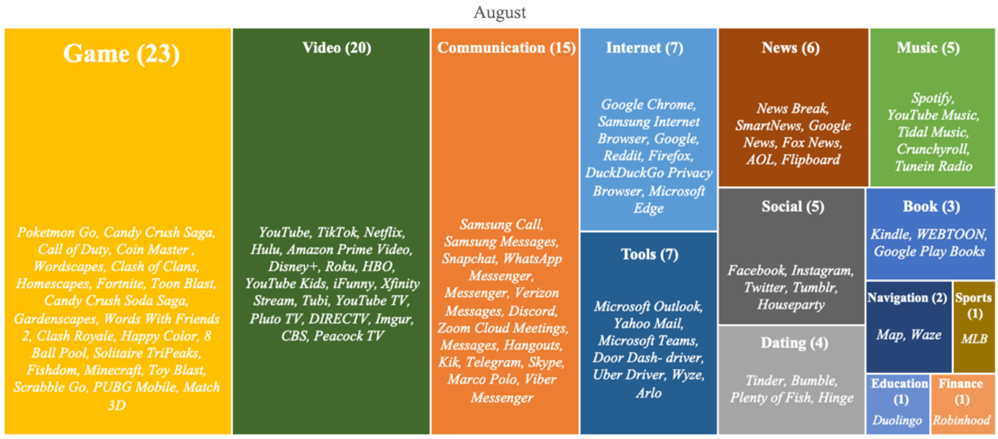
Table 1. *Cont.*

	January	August
79	Best Fiends—Free Puzzle Game	Solitaire TriPeaks: Play Free Solitaire Card Games
80	Fortnite	Wyze
81	Crunchyroll	Flipboard—Latest News, Top Stories & Lifestyle
82	Fishdom	Spectrum TV
83	Spectrum TV	PUBG MOBILE—NEW ERA
84	Hinge—Dating & Relationships	Crunchyroll
85	Archero	8 Ball Pool
86	Microsoft Edge	MLB
87	Wyze	YouTube TV—Watch & Record Live TV
88	Bricks Ball Crusher	Minecraft
89	Happy Color™—Color by Number	Duolingo: Learn Languages Free
90	TuneIn Radio: Live News, Sports & Music Stations	Match 3D—Matching Puzzle Game
91	DIRECTV	Arlo
92	Tubi—Free Movies & TV Shows	Imgur: Find funny GIFs, memes & watch viral videos
93	Word Stacks	Houseparty
94	Pluto TV—Free Live TV and Movies	TuneIn Radio: Live News, Sports & Music Stations
95	Minecraft	Tubi—Free Movies & TV Shows
96	Sniper 3D: Fun Free Online FPS Shooting Game	Google Play Books—Ebooks, Audiobooks, and Comics
97	Game of Thrones: Conquest ™—Strategy Game	Pluto TV—Free Live TV and Movies
98	BitLife—Life Simulator	DIRECTV
99	Solitaire	CBS—Full Episodes & Live TV
100	CBS—Full Episodes & Live TV	Peacock TV—Stream TV, Movies, Live Sports & More



(**a**) Tree map in January.

Figure 4. *Cont.*



(**b**) Tree map in August.

Figure 4. Tree map of ranking in January and August.

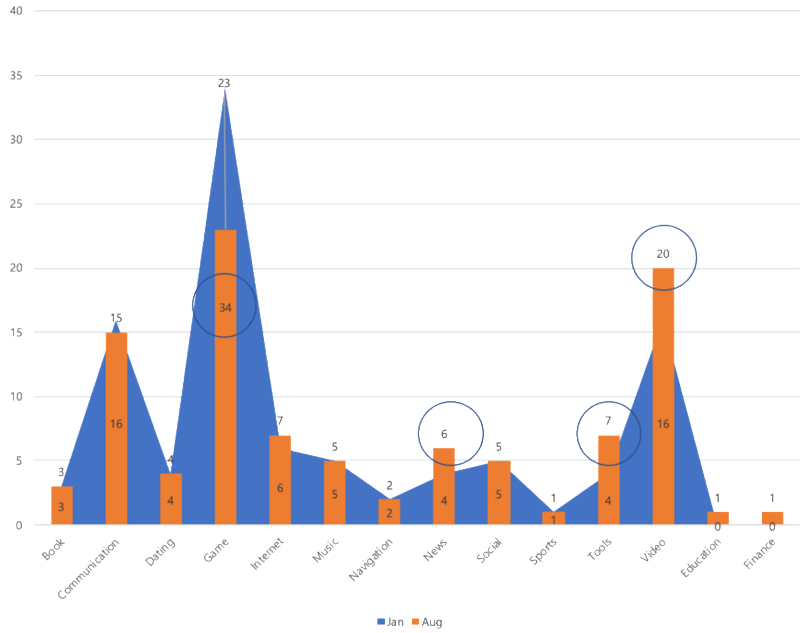


Figure 5. Graph describing top 100 applications list between January and August 2020.

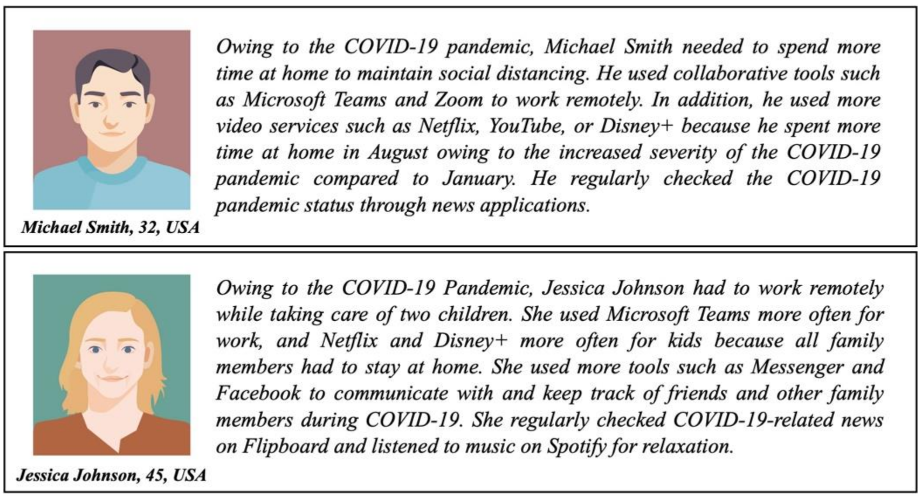


Figure 6. *Cont.*

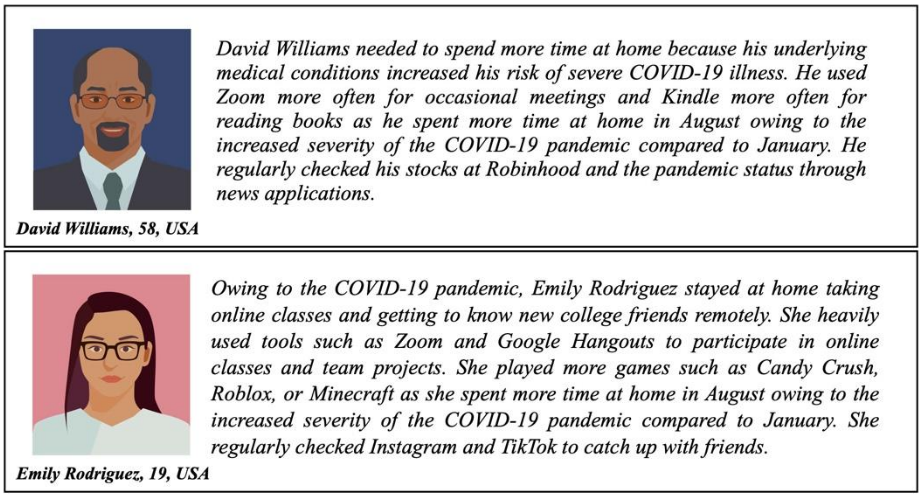


Figure 6. Four different types of personas in August 2020 constructed through analysis of data from January and August 2020.

5. Discussion of Creating Personas Using Mobile Application Store Data

To validate the resultant personas created, we used the expert interview method based on the method used in Zhang, Brown and Shankar's study [25] and Minchiello et al.'s study [34]. We conducted expert interviews with eight experts involved in smartphone development and marketing (mean age: 43, six males and two females). The recruited experts have more than 10 years' experience in the UX and lifestyle research area. Expert interviews were generally conducted as semi-structured interviews. Interview questions were generally presented verbally. In addition, the explanations behind the created personas were presented through a slideshow. Interviews were recorded and analysed by the experimenters to find insights. In general, expert interviews were conducted to identify the application usage trends' change between before COVID-19 and during COVID-19. In addition, we revealed our new method to create a persona using smartphone store data. We identified the advantages and disadvantages of the new method through expert interviews. Table 2 presents the questions list for the expert interview.

Table 2. Questions list for the expert interview.

What were the mobile phone usage trends before COVID-19?
What were the mobile phone usage trends during COVID-19?
Describe the traditional method to create personas for mobile phone developers.
We propose the new method to create personas using application store data for the smartphone developers, designers, and marketers. Give us your impressions of it.
Tell us if the generated personas from this new method are consistent with the current application usage trends under COVID-19.
Describe the advantages and disadvantages of the new method in creating personas.

Initially, we reviewed two lists between January and August to observe lifestyle changes arising from the COVID-19 pandemic (Figures 4 and 5 and Table 1). First, all experts agreed that the created persona could reflect the impact of the COVID-19 pandemic effectively. It is self-evident that the severity of the COVID-19 pandemic led people to spend more time at home to maintain social distancing or to work remotely, so people used more video-related applications, such as YouTube, Netflix and Disney+. In addition, they agreed that remote working was preferred during the pandemic lockdown, so people used collaborative tools, such as Microsoft Teams or Zoom, more often. All experts suggested that an approach that uses mobile application store data to create personas has advantages as well as disadvantages. In terms of advantages, experts agreed that this approach could see the complete picture of lifestyle change through mobile phone usage. Mobile phones are the most important device for daily life, so the changing trends of application usage reflect the change in user characteristics and user behaviours. In addition, using mobile application data is a good way to create quantitative persona creations. It can support the designer's ideas with a large amount of data. Thus, it can provide powerful evidence for design-related decisions.

However, several weaknesses were also suggested by experts. First, this approach cannot create personas automatically. When data collection is completed by the system, the designer needs to calculate the ranking and extract the insights, after which the designer can create the persona. This process is complex and not easy for the average designer. In the future, an automatic persona creation [26] function based on the data should be developed to support designers.

Second, the designer cannot understand the reason for the trends change. The system only provides data while the designer needs to calculate a ranking. Consequently, extracting insights depend on the designer's ability. For example, the game category decreased in August compared with January. The designer assumed that the market of mobile phone games had decreased. Gamers prefer PC or console games at home because PC or console games provide bigger screens and higher immersion during playing compared with mobile phones. Several news items reported that spending more time at home induced more video game playing. Global game industry sales have increased to $10 bn each month since March, with sales growing each month [35]. Thus, designers must check reports or news to determine the reason behind changes in mobile application usage. Therefore, in the future, combining news or buzz data of social network systems should be considered, as this may aid designers in understanding the reasons for certain changes and help them gain more useful insights.

Third, our novel method to create personas using a smartphone application store applies a calculation of top-n ranking. To calculate top-n ranking, we suggested a new formula that considered three different attributes, i.e., the number of devices that used each application, the number of times the application was used and the application usage time. If the formula considers other types of attributes, the ranking can be changed.

Fourth, in order to guarantee the accuracy of the formula when calculating the data distribution from the mobile application store, the ecology change in the mobile application market must be tracked over a long time.

Finally, we used WDA as a framework to present the method to create personas using application store data. The main advantage of WDA is that it enables the depiction of the work domain in its entirety at various levels of abstraction [36–38]. However, in our research, the framework using WDA did not involve all kinds of data attributes from the application store. Furthermore, WDA is a useful framework for cognitive engineering experts. Hence, we believe that the process of decomposition may be difficult for experts unfamiliar with WDA, such as designers or marketers.

In the future, we should collect more demographic information on mobile phone usage. Although we added some demographic information to the new persona development framework in WDA, we could not use more demographic information because the data agency did not collect it. This requires verifying the usefulness of demographic information to generate personas by using application store data. In addition, using advanced AI technology, the generated persona can have a more specific personality based on other data [39,40]. Thus, the persona generated from the mobile application data can be combined with the personality generated from the social network data. The study of Hu et al. suggested measuring brand personality using social media data [41]. This can help marketers and application designers to develop strategies for mobile applications and marketing strategies. For example, designers can use a data-driven persona at the initial stage of ideation to develop new smartphone applications, while marketers can set up the target customers at the last stage of releasing the application in order to advertise them.

6. Conclusions

As mobile phones are regarded as the most important device reflecting the user's daily lifestyle, the importance of quantitative persona creation has dramatically increased in the market. However, there is a research gap as regards using mobile application store data to create quantitative personas. In order to create a quantitative persona by using data from the mobile phone application store, we propose a new framework. The proposed framework provides a method to use various data from the mobile application store, and these data can be analysed. Based on the new framework, we also define the process of persona creation using smartphone application store data. Unlike other studies [17,25,42], we focused on extracting either the usage patterns or trends from smartphone usage habits. This involves not only the quantitative persona creation process using mobile application store data but also the proportion of use in terms of three major datasets: the number of devices that used the specific application, the number of times each application is used per device and the usage time of each application. We determined the list of top 100 applications by applying the framework and then constructed a quantitative persona based on the data analysis. To validate the result of the quantitative persona creation, we conducted expert interviews. The result of the interview indicated that quantitative persona creation based on the mobile application store data reflected the change in lifestyle effectively. However, some improvements to this work were suggested. First, the system should be able to create quantitative personas automatically. Although this research was designed to assist designers and marketers, it is still difficult to discover insights and follow the process of quantitative persona creation. Second, the method of quantitative persona creation should also consider news or social network buzz data to determine potential reasons for lifestyle changes in mobile application usage. Thus, the persona generated from quantitative data should be combined with qualitative data to make it more meaningful. Third, ecology changes in the mobile application market should be tracked regularly to improve the accuracy of the formula when calculating data.

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