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Fast track article

Mobile app adoption in different life stages: An empirical analysis

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ABSTRACT

The analysis of individuals' current life stages is a powerful approach for identifying und understanding patterns of human behavior. Different stages imply different preferences and consumer demands. Thus, life stages play an important role in marketing, economics, and sociology. However, such information is difficult to be obtained especially in the digital world. This work thus contributed to both theory and practice from two aspects. First, we conducted a large-scale empirical study with 1435 participants and showed that a person's mobile app adoption pattern is strongly influenced by her current life stage. Second, we presented a data-driven, highly-scalable, and real-time approach of predicting an individual's current life stage based on the apps she has installed on smartphone. Result showed that our predictive models were able to predict life stages with 241.0% higher precision and 148.2% higher recall than a random guess on average.

1. Introduction

Research on people's life stages can be traced back to the early 1930s. It started in sociology and then entered marketing research to explain behavioral differences among people at different stages. Researchers in fields like insurance [1], healthcare [2], and retailing [3] claimed that life stages have a significantly impact on individual's choice of decision-making. For Instance, young families buy baby food, do not dive into nightlife, and prefer to travel locally [4], whereas singles without children tend more to eat outside, experience new things, and travel around the world. Contemporary traveling-related patterns were examined by Collins and Tisdell in 2002 [5].

Based on the known life stage, companies can offer personalized product recommendations or conduct better segmented-marketing to improve customer satisfaction or to reduce costs [6–9]. However, an individual's current life stage remains unknown until being measured. Questionnaire and face-to-face interviews have been widely used in research and practice to gain knowledge about one's life stage [10]. But the downside of those approaches is obvious—it is costly and not scalable [11].

With the fast penetration of digitalization in our daily life, life stages become more difficult to know in the digital world because we cannot even guess one's life stage from her look and feel. However, digitalization on the other hand also brings new opportunities. Recent research in reality mining has shown a possibility to predict a smartphone user's demographics, interest, and personality based on her phone logs or apps installed [12–15]. As smartphones are the most personal devices we own and the apps we install reflect our preference and behavior [16], we thus suspect that it is possible to predict a smartphone user's current life stage by analyzing the installed mobile apps in real-time.

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For a thorough investigation, a large-scale field study was conducted with 1435 participants. As a first step, people's adoption behavior in different life stages is analyzed to examine whether an individual's app installation behavior is significantly associated with her current life stage. To the best of our knowledge, no study has been conducted to understand the relationship between app adoption patterns and different life stages. The present paper tries to address the research gap. In a second part, a predictive model for determining an individual's life stage is developed. The model is evaluated and compared with a random guess. Results show that user's app adoption behavior can serve as useful feature to predict her current life stage, which enables a whole bunch of new research and business opportunities.

The rest of the paper is structured as follows: The related work section reviews previous literature on background of life stage research, life stage prediction, reality mining, and app adoption. Afterwards, we explain our research design before presenting the research results. In the last section, we discuss privacy aspects and limitations and provide an outlook on future works.

2. Related work

2.1. Life cycle analysis

The concept of life cycle was introduced in sociology in the early 1930s by Sorokin et al. [17]. His work was the starting point for the so-called academic rural sociology, which tried to respond to urgent contemporary questions related to poverty, migration, and revolts. Twenty years later, the concept of life cycle found entrance into the marketing research. A life cycle contains several life stages like having family or getting retired. During lifetime, individuals move from one stage to another, triggered by major life events like having a first child or retiring. Lansing and Kish [18] called it 'family life cycle'. They claimed that people's attitude and behavior might be associated less with the biological process of aging, but more with the individual family status. Lydall [19] and Lansing and Morgan [20] discovered the correlation between life cycles and financial factors like income, saving, and asset ownership.

Baek and Hong [21] found that life stages are a significant factor that affects an individual's installment debt and credit card debt, which contributes to practical implications for financial counselors and educators, lenders, consumers, and policy makers. In insurance industry, researchers argued that changes in life stages significantly impact an individual's choice of different insurance products [1,22]. Artle and Varaiya [23] revealed the fact that people in different life stages have different consumer behavior related to homeownership. Rabe and Taylor [24] supported such arguments with a panel study on British households and found that couples who have new babies are more likely to move into a better neighborhood.

Research in the field of life stages has a long tradition and its findings are still of high relevance in many industries today. It helps to understand hidden mechanisms in the whole societies as well as the behavior of an individual. However, there is no common definition of life stages in previous literature. Lansing and Kish [18] proposed nine life stages including marital status, children, and age. Wells and Gubar [25] supported the use of additionally information about people's working life with the same number of life stages. The established model of Gilly and Enis [26] incorporated the increasing number of single-person house-holds, cohabitation by non-legally married adults, delayed parenting, and rising divorce rates. Wilkes [27] studied expenditures across the life cycle by dividing the people in three main groups ('under age 35'; 'age 35+, not retired'; 'age 35+, retired') and 15 subgroups, again with a focus on marital status, children, and age. Du and Kamakura [28] suggested 13 life stages and considered different household sizes in his model.

In 1966, Wells and Gubar already recognized that the definition of life stages (hereinafter referred to as categories) is not trivial: "If a category is too narrow, it will include such a small proportion of the sample that it will be all but unpopulated except large surveys. If it is too broad, it will cover such a wide variety of consumers that it will not identify anybody. And, if it is inappropriately selected, so that it merges groups with very different consumption patterns, it will not discriminate no matter how broad or narrow it is". [25] In addition, the authors mentioned the problem with people who do not fit into one of the defined life stages. They proposed to force them into one of the defined stages or to remove them from the study.

2.2. Life stage prediction

In summary, people in distinct life stages have different consumer behaviors. Therefore, knowing the current life stage of an individual can lead to new business or marketing opportunities. Thanks to a better customer segmentation, personalized product recommendation can be offered with a higher accuracy. But until today, most of the studies regarding life stages are limited to descriptive level. Kapinus and Johnson [29] reviewed the utility of family life cycles and demonstrated the usefulness as a predictive tool. Nevertheless, scientific publications that go a step further and try to predict individuals' life stages are scarce. As one of the few studies, Jiang and Zhu [30] built a Maximum Entropy Semi Markov Model to segment and predict life stages based on observed purchasing data. They suggested to use their concept in recommender systems and presented its effectiveness in offline and online experiments. Du and Kamakura [28] developed also a Markov Model, but for the opposite purpose: They used historic data from US households for a period of 34 years to identify empirically the most typical life stages and the transition probabilities in between. Then, the authors suggested firms to predict expenditures on durable goods based on customers' most likely life stage.

Bayer [31] applied a path analysis to predict a specific life stage change: the marriage. Out of four independent variables, the expected age at marriage, stated some prior to marriage, was the best single predictor. Yang [32] observed and analyzed data from panel interviews and surveys about consumption of housing and non-housing goods and developed a quantitative, dynamic, and general equilibrium model to predict life cycle behavior as well as to generate consumption profiles.

By utilizing location telematics data, it is also possible to predict changes in life stages in real-time. For instance, if a person travels to properties that are for sale with certain degree of frequency, analysis engine may determine that she is in the market for new home. It will then recommend targeted advertising or products (e.g. home inspection, mortgage products) to her [33].

Despite limited number of studies, the referenced work suffers under several problems. First, many studies used anonymized and historic data that is not usable for real-time applications, in particular for customer feedback. Second, some of the predictors used in those studies are difficult to detect until being measured in questionnaires or interviews, which are often painful, time-consuming, and limited scalable [11]. Third, existing research uses questionnaire to collect ground-truth, which is costly and not scalable. Also, using questionnaire as a research method cannot exclude the intention-behavior gap. Forth, some of the data is only available to selected companies such as wholesaler, credit card providers, vehicle manufacturers or telecommunication companies and not for other market players. These issues strongly limit the use of proposed methods in practice.

2.3. Reality-mining on mobile devices and app adoption

The usage of mobile devices such as smartphones and tablets has increased massively in the past decade [16]. It enables new ways to observe and study people's behavior, habits, interests, and needs. It was never easier to collect personal data and to derive valuable information for customers, companies, governments and research in real-time. It motivates researchers to explore and present several reality-mining methods. The prediction of demographics like age and gender is one of the preferred disciplines. For this purpose, researchers leveraged acoustic measurements [34], phone call logs [35,36], social network content [37–39], email content [40], face recognition [41], and many more. Pan et al. [42] accurately predicted events like what mobile apps a user would install in the near further by using a composite network computed from the different networks sensed by phones.

While the methods above may trigger strong privacy concerns, some researchers thus proposed a less intrusive method to gather useful data. They recommended to leverage the list of installed apps on mobile devices as a data source to infer user profiles. There are more than a million apps available in app markets [43] and there is one for almost any situation in our life. Thus, the list of apps on mobile devices is very personal and unique [44]. Seneviratne et al. [12] predicted personal traits like religion, relationship status, and spoken languages. A similar study combined observed patterns in the set of installed apps with the adoption theory [15]. The authors showed that it is possible to determine a user's big five personality traits in reasonable accuracy by evaluating her history of app installations and update events. Other studies analyzed the app usage in general [45], users' update behavior [46], and their handling of permissions [47]. Frey et al. [48] promote the list of installed apps as a lightweight user tracking method for app providers and further, as an instrument to build digital inventories of physical objects [49].

A new study predicts semi-automatically major life events like buying the first car or getting married, again based on installed apps [50]. The training of these models is extremely difficult, because such events are rare by definition. A long observation time is required and even then, the event can be too short to get a significant impact on the collection of installed apps. Fortunately, this is not the case for life stages, where people are in for years. We hypothesize that different living circumstances are significantly reflected by their app adoption behavior. Leveraging information about what apps a smartphone user has installed could contribute to the prediction of the user's current life stage. Such a reality mining approach contributes to overcome the limitations of current life stage prediction methods, as we introduced in the end of last subsection. To the best of our knowledge, predicting life stages in real-time in a scalable and fully automatic way is not yet available in both academia and practice. Consequently, we try to address that research gap in the present study.

3. Research methodology

3.1. Research question and design

The concept of life cycle is a well-established, 80-years old research area, as shown in the previous section. Its usefulness and impact on people's behavior are undisputed today. Thanks to new technologies and the digitalization of people's life within the last decade, we now have access to a mass amount of data in digital forms. We suggest to combine the concept of life cycles with one of the most widely used technical gadgets in people's daily life, mobile devices like smartphones and tablets. Since the collection of installed apps reflects the preference and behavior [16] of the user, we hypothesize that the app adoption behavior is strongly influenced by a user's current life stage. Thus, the first research question is as follows:

RQ1: How does users' mobile app adoption behavior change according to different life stages?

However, research in this area in the past was mostly limited to descriptive investigations. Neither were data samples available near-term, nor were applications out in the market to prove the usefulness of the models. Real-time predictions of a consumer's life stage and resultant product recommendations were crucial to a company's success but not yet well

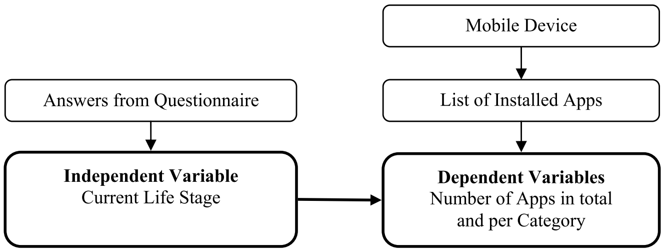


Fig. 1. Data model for each participant.

addressed in both research and practice. We hypothesize that leveraging information about who installs what app is already sufficient to predict an individual's current life stage. Consequently, we aim to answer the second research question:

RQ2: How accurate can a users' current life stage be predicted based on her app adoption pattern?

To answer the both research questions in an empirical study, two types of data will be collected. First, a questionnaire is presented to each participant to gather ground-truth about her current life stage. Second, the installed apps on an individual's mobile device are collected. Due to the fact that there are more than one million mobile apps on major app markets, it becomes impossible to analyze all the apps at the same time. Therefore, we automatically convert all apps into categories to gain broad and general knowledge about one's app installation behavior. After acquiring the data, the association between life stages and the number of apps per category is analyzed and a predictive model is built and evaluated. Fig. 1 presents an overview of the described data model.

3.2. Data collection method

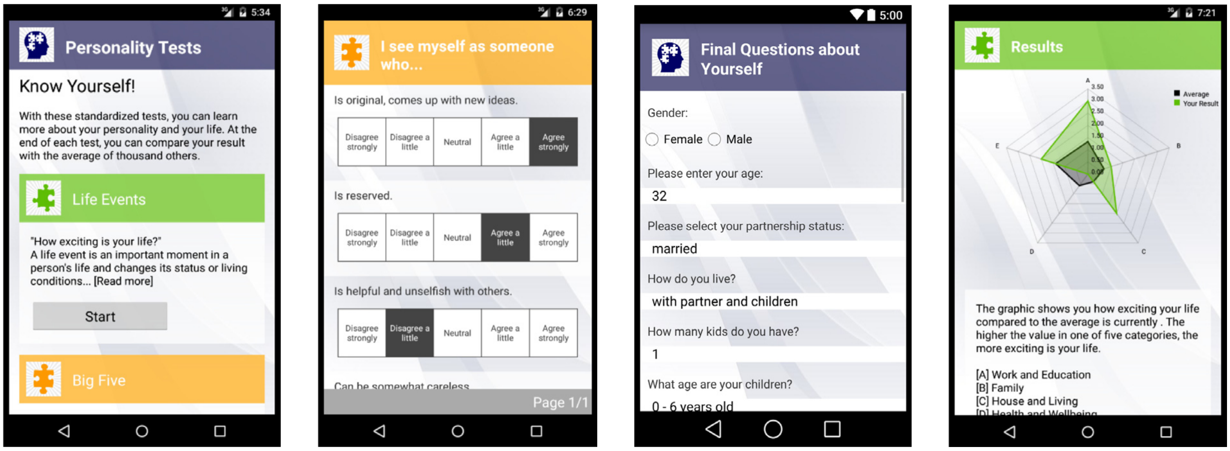
We developed a mobile app for the Android operating system to collect both types of data for this research study. The app is described as a test game, where users provide answers to different personality and life event questions with the aim to know more about themselves as well as to compare their results with the average values of other people who also use the app. Fig. 2 shows four screenshots of the app. When the app is opened for the first time, the user is requested to accept the privacy policy. If the user rejects the privacy condition, the app is forced to quit and no data will be collected and analyzed. If the user accepts the privacy terms, a background process is initiated, which retrieves the app installation logs from the device: Android provides a public API called 'android.content.pm' to read the list of installed apps. Besides other data, the list contains app name and package name. We consider only the package name because it is a unique identifier. The list is send directly to our backend webserver and stored in a database. Meanwhile, the user is on the landing page, as shown in Fig. 2(a), where she can choose between several personality tests. Each test is shortly explained and contains a questionnaire. A screenshot of a questionnaire about personality traits is shown in Fig. 2(b). At the end of the first completed questionnaire, questions about demographics are displayed to the user, as shown in Fig. 2(c). The demographics are used for defining the life stages. The variables are: age, gender, country, job, salary, education, partnership, age of kids, and household. The distribution of their values is shown in Table 1 in the result section. Finally, the app displays the results of the personality tests and compares the answers with the average of the other people who have already participated in the game. As shown in Fig. 2(d), the results are illustrated by a spider graph. It is the main incentive to the users and they do not receive monetary compensation.

Once all the questions of a questionnaire are answered, the answers are transmitted immediately to our server. It is impossible to redo the questionnaire on the same device more than once. In addition, if the user goes to the next page inside a questionnaire, it will not be possible to go back to change answers. By these restrictions, we prevent users from providing their own device to others who also want to do the test. The app is listed on Google Play Store for free usage. We leverage Facebook pages, news feeds and posts to encourage users to download the app. Details about the promotion are provided in the result section.

After collecting data, participants who fail to answer all the questions that sample life stages are excluded in the analysis. To control the quality of our study, we also add an attention test, a simple mathematic problem ($3 + 7 = ?$), in the questionnaire to screen out irrational answers. The remaining data points can be used to analyze different app adoption between individuals at different life stages. The sampled life stages also serve as ground-truth to train and test our predictive model.

3.3. Life stage definition

In the present work, the goal is to consider common and well-known life stages with the aim to demonstrate the different adoption behavior on it. Life stages are the independent variable. Therefore, this variable is defined *before* the dependent variables are viewed and analyzed. However, defining a finite set of life stages is a non-trivial task, as described by Wells and Gubar [25] in Section 2.1. There are no widely adopted categories of life stages yet, but novel data driven approaches helps to identify empirically the most typical stages. Du and Kamakura [28] used a hidden Markov model to identify latent



(a) Landing page.

(b) Questionnaire about personality traits.

(c) Questionnaire about demographics.

(d) Results illustrated by a star graph.

Fig. 2. Screenshots of the mobile app for collecting the study data.

stages and connections out of ten common demographic characteristics in the United States. The relevant dimensions are relationship, children and household. We decided to use their definition because our participants are located in a western country as well. But, their complex graph with 13 life stages and 17 connections should be manually simplified according to our study objectives and collected demographics. In detail, we intend to reduce the number of stages from 13 to a maximum of six. Six stages are expected to be sufficient for answering the research questions and for the visualization of the results in a life cycle with 5 connections. A higher number of life stages would reduce the observed differences between the stages, would need more study participants, and would increase the result volume and complexity of the whole article unnecessary. The number of stages will be condensed so that the number of samples in each stage has an acceptable size and the number of samples who do not fit into anyone of the stages is low. As a second simplification, we do not distinguish between 'in a relationship', 'married', and 'divorced' because marrying is no longer a premise for living together as a couple or having a child in western societies today, according to Sobotka and Toulemon [51]. The authors observe an overwhelming 'decline of marriage' in Europe in the past decades. Fewer people are living together in marriage and more children are born outside marriage. Thornton, Axinn, and Xie [52] report similar trends in the United States and note that "marriage has become less central in organizing economic production, consumption, and the transfer of property across generations".

3.4. App categorization step

To the best of our knowledge, there is no scientific categorization of mobile apps. To keep our approach applicable for all mobile app developers, we choose to use open-accessible data to categorize mobile apps into categories. Two different methods are applied.

First, the categorization of the apps is done by the developers themselves when they publish their apps on Google Play Store. The current app categorization on that store was taken as a standard due to its popularity among app developers and publishers. There were in total 47 categories on Google Play Store—24 main categories, 17 subcategories for mobile games, and 6 subcategories for family apps (retrieved in July 2015). Our task was then just to read the information out of the official online platform of the store. This process can be achieved automatically. In the present work, this kind of categories is called 'developer-tagged'. Two additional main categories are added: 'Games' and 'Family'. These two categories are the union of the subcategories for games and families.

However, the developer-tagged main categories are in many cases too general to capture the different types of apps. Therefore, we decided to use a second way to categorize apps, based on the app descriptions on Google Play Store. The app descriptions can be collected automatically from its online platform. There are several scientific articles which describe how to use such data for app categorization [53–56]. Since app categorization is a different story and not the focus of this work, we used existing results from our research partners: They provided a list with the 71,453 most popular apps on Google Play Store and 140 corresponding categories. The apps were categorized by a method using the app description according to the work of Berardi et al. [56]. As a cleaning step, we removed categories which were either similar to each other (e.g. 'Image Editing' versus 'Photo editing'), similar to the 'developer-tagged' categories (e.g. 'Weather' versus 'Weather Forecast'), unclear (e.g. 'Free Calls', 'Speed Camera') or too specific (e.g. 'Jazz', 'Chemistry'). We called the remaining 86 categories 'description-based'. Since the granularity is higher with these additional categories, a more detailed interpretation of the results is expected. The full list of the used app categories for both methods – 'developer-tagged' and 'description-based' – is provided in the Appendix.

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3.5. Data analysis

As previously described, reported demographics are used to group the participants into different life stages. 'Life stage' is used as independent variable. The amounts of observed apps per category are used as dependent variable.

To answer the first research question, we descriptively analyze the collected data. First, we compute the adoption rate for each category and life stage. A user is considered as an adopter if there is at least one app from that category on her device. Second, we predefine a typical life cycle where all life stages are part of it and compare life stages which lie adjacent one another. In doing so, we track the chronological changes between the life stages during the whole life cycle. To compare neighboring life stages, the usage of the t-test [57] is the appropriate statistical instrument. Note that we consider the number of apps a user has installed per category and not just the simplified adoption rate. Since the average number of apps on a mobile device is smaller than the numbers of categories we analyze, a median around zero, a non-normal distribution (skewed), and large tails are expected for the most categories. Therefore, the normality assumption for t-test should be checked by the Shapiro–Wilk test [58]. In case of non-normality, the Mann–Whitney U test [59] is a non-parametric alternative to t-test. The test can often have three or four times higher statistical power than t-test [60–62]. There are four assumptions related to Mann–Whitney U test: The dependent variable should be ordinal or continuous; the independent variable should consist of two categorical groups; independence of observations; and the distributions should have the same shape. The first three assumptions are obviously fulfilled based on our study design. The fourth assumption is required for comparing the medians of the two distributions. It should be checked by the Kolmogorov–Smirnov test [63]. If the fourth assumption does not hold, we reduce the interpretation on the comparison of the mean rank. Additionally, we provide the effect size according to Rosenthal's formula [64] to demonstrate how strong the differences between two stages are.

In terms of predicting life stages, input features of our predictive model are the number of apps in different app categories. Because the relationship between behavioral factors and life events could be non-linear, we use the Random Forest algorithm [65–67] in the modeling due to its ability to capture both linear and non-linear relationships. Although Random Forest not performs best for any given data set in previous works, Fernandez-Delgado et al. [68] claims after an extensive evaluation of 179 classifiers and 121 data sets that Random Forest is most likely to be the best in terms of accuracy. Caruana et al. [69] conducted a similar evaluation and observed that Random Forest performs consistently well on high-dimensional data. In addition, Random Forest provides insights on what factors are more important in model generation [65] and it robust to noise and overfitting [65–67], which makes models less sensitive to variance. Another advantage of Random Forest is that the evaluation on new data can be done fast, because the algorithm is parallelizable [65]. Each tree can be evaluated separately. Quickness is important for real-time applications. A typical application of our work is using the trained models in a recommender system. Reading the apps, classifying the user in one of the six life stages, and providing personalized recommendations should be done without the user noticing a delay. Finally, Random Forest is simple compared to other methods [65], which means that it is easy to build a good model while other methods struggle with the right parameter tuning. And, a Random Forest algorithm can be written in a few lines of codes. Simplicity is important for the appliance of our work in practice because our method can be used by any app provider, not only by large companies with large resources and know-how.

To answer the second research question, we divide our data samples randomly into two sets: 70% samples in a training set and 30% samples in a test set. Parameters of the predictive models like number of predictors to consider at each branch split in Random Forest is tuned through cross-validation [66,67] on the training samples. The best-performed model is then applied on the separate test data set to check the prediction precision, recall, accuracy, and specificity.

4. Results

4.1. Samples

We published our survey app for free on Google Play Store. The app was available in two countries (USA and Germany) on two continents and two different languages (English and German) in order to demonstrate the robustness of our method related to culture and language. We promoted the app through Facebook posts and feeds for two weeks in August 2015. During this period, our app promotion page was shown to 211,090 people and 1465 people installed the app. The conversion rate for installation was around 2%. Further, 520 people installed the app directly from Google Play without being reached by our Facebook feeds. In the present study, we used data collected between August 13, 2015 and November 11, 2015. In total, there are 1896 users who accepted our privacy policy. 1459 people answered the demographic questions which include all questions about life stages. Two people are removed because they used an obsolete version of our app and 22 people failed on our attention test. Thus, we finally had 1435 usable samples. The demographics are summarized in Table 1.

4.2. Life stage definition

According to the approach introduced in Section 3.3, we defined six life stages. The stages are shown in Table 2. The number of samples who do not fit into one of the stages is 268.

Table 1
Characteristics of participants in the study ($N = 1435$).

Age	10–19 34%	20–29 38%	30–39 16%	40–49 5%	Others 7%	
Gender	Female 75%	Male 25%	Country	Germany 45%	USA 53%	Others 2%
Job type	Pupil/student 27%	Full-time job 38%	Part-time job 8%	Job-seeking 6%	Homemaker 8%	Others 13%
Net monthly salary	Less than 500 25%	500–1000 18%	1000–1500 16%	1500–2000 13%	>2000 12%	No answer 15%
Highest education	No degree 7%	Elementary school 2%	Middle school 26%	High school 38%	Vocational school 15%	College/university 12%
Partnership status	Single 39%	In a relationship 40%	Married 14%	Divorced/separated 3%	Widowed 0%	No answer 3%
Age of kids	No children 67%	0–6 years 16%	7–14 years 9%	15–18 years 3%	>18 years 4%	
Household	Living with the parents 40%	Living with partner 17%	With partner and children 16%	Single parent 7%	Shared apartment 10%	Living alone 12%

Table 2
Life stages used in the present study.

Life stage	Description	Number of samples
A	Teenager (15–19 years old), living with the parents	349
B	Single without children	210
C	Couple without children	278
D	Family with children younger than 15 years	196
E	Family with children equal or older than 15 years	56
F	Single parent	78
–	Others	268
	Total	1435

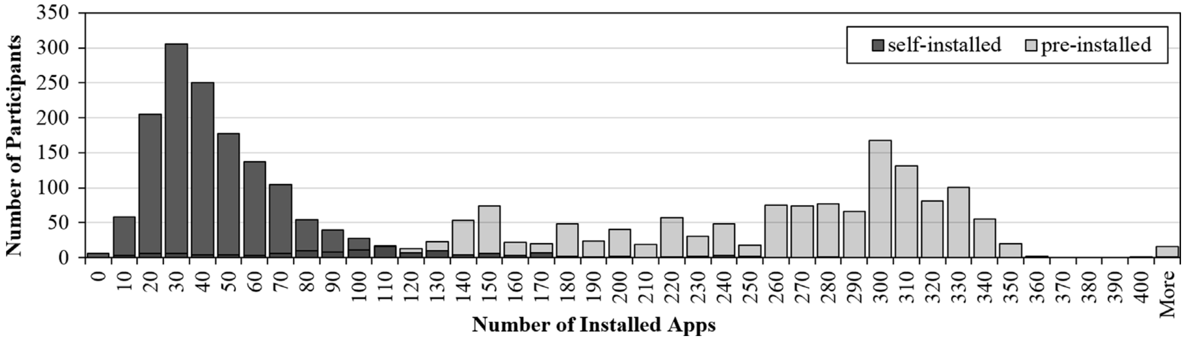

Fig. 3. Distribution of self-installed and pre-installed apps per participant ($N = 1435$).

4.3. Mobile app adoption

As described in Section 3.2, we collected the list of installed apps on the devices of our participants. On these 1435 devices, we counted 422,143 apps in total, among which 63,427 were self-installed. In our study, we considered only apps which had been installed by the users themselves and not pre-installed by the manufacturer or dealer. Pre-installed apps were tagged as such on the mobile device. This information is freely accessible for each app installed on the device. Fig. 3 shows the distribution of all apps, separated in self-installed and pre-installed. It is clear that the number of pre-installed apps is surprisingly large compared to self-installed apps. The reason is that many pre-installed apps are system tools like 'Package Installer', 'Proxy Handler', 'Bluetooth Share', 'Settings', 'Display Timeout Widget'. Some of these apps run in the background and are not visible to the users. We assume that such apps have negligible impact on the adoption behavior or even blur the real adoption behavior. Therefore, we focus on self-installed apps.

On Average, a user has 44 apps self-installed and 250 pre-installed, as shown in the pie chart on Fig. 4. In addition, the pie chart displays how many apps are running on average in the moment we caught the data. Running apps are tagged as such

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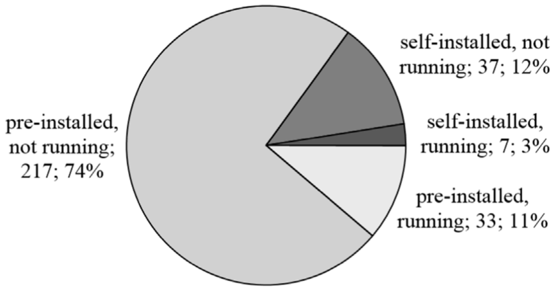

Fig. 4. Who installed the apps on a mobile device and how many apps are running on average? Absolute and relative numbers are displayed.

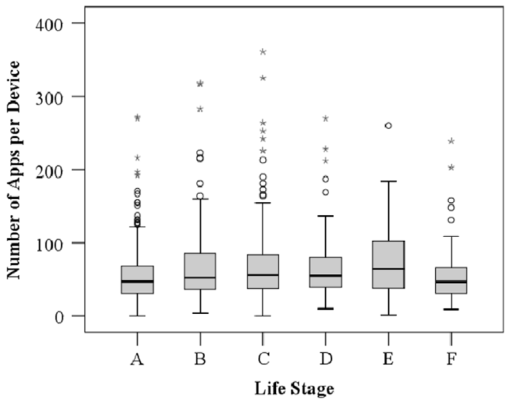

Fig. 5. Distribution of the number of self-installed apps per device in different life stages.

analogue to pre-installed apps. Since the observation of running apps in a single point in time does not adequately reflect the overall adoption behavior, we do not consider this information in the further analysis. Fig. 5 shows the distribution of the number of self-installed apps in the six different life stages. The box represents the interquartile (IQ) range containing the middle 50% of the records. The whiskers comprise values not greater than 1.5 times the IQ range. Circles marks outliers with values between 1.5 and 3 times the IQ range. Extremes cases are marked by stars. A Kruskal–Wallis H test shows that there is a statistically significant difference in number of apps between the different life stages, $\chi^2(5) = 29.682$, $p < 0.001$, with a mean rank of 512.91 for stage A, 613.30 for stage B, 629.63 for stage C, 616.47 for stage D, 662.65 for stage E and 522.51 for stage F.

We counted 18,312 unique apps in 135 categories. There were 27 distinct categories on average on each mobile device. Fig. 6 shows the 40 most popular categories without Google's subcategories. 'Games' is by far the most frequent category, followed by 'Lifestyle' and 'Instant Messaging'. Due to the massive proliferation of games, we consider the game subcategories separately. Google's family subcategories are interesting as well, because two of our predefined life stages are involving families. To prevent an overload with extensive result tables in this article, the analysis in the next sections is limited to these 40 categories and the subcategories for games and families. The prediction part at the end of the result section will then use all categories (and subcategories) again.

4.4. Life stage dynamics

In this section, the differences of app adoption in different life stages are investigated. A typical life cycle is displayed in Fig. 7, based on the predefined life stages. During peoples' life span, they go from one stage to the other. While this process is ongoing, the interests, habits and needs are changing gradually and thus, also the installed apps on individuals' smartphones. According to the described method in the data analysis section, pairwise comparisons are conducted to examine different app installation behaviors among people at different life stages. Since the Shapiro–Wilk test confirms non-normality for most categories, we chose the non-parametric Mann–Whitney U test, as discussed in the data analysis section. The mentioned Kolmogorov–Smirnov test indicates that the assumption related to the distribution is violated in most cases. Therefore, we have to reduce our interpretation on the comparison of the mean ranks instead of medians.

As mentioned, the focus lies on the difference between two continuous life stages. Counterintuitively, the difference is already big and significant. In Fig. 7, all significant differences are depicted in the rectangular boxes. The non-significant differences are omitted for better readability. Table 3 provides the results of all 40 investigated app categories, plus the subcategories about games and family. Besides the comparisons, the adoption rates for all categories are shown as well.

Table 3
The table displays the app adoption rate of each life stage ($N = 1435$) and the comparisons between any two neighboring life stages. The highest adoption rate in each category is marked in bold. Comparisons are made by Mann–Whitney U tests: U-value, effect size r, and the mean rank difference Δ are displayed for each of the five comparisons.

Category	Adoption rate per stage						A vs. B			B vs. C			C vs. D			D vs. E			D vs. F		
	A	B	C	D	E	F	U	r	Δ	U	r	Δ	U	r	Δ	U	R	Δ	U	r	Δ
Automobile	.13	.15	**.22**	.21	.11	.18	35 752	.03	7	**26 932***	**.10**	**19**	26 702	.02	−5	4913	.11	−13	7458	.03	−3
Books & reference	.37	.40	.41	.36	**.46**	.37	34 469	.05	15	28 642	.01	2	25 740	.04	−10	4710	.10	15	7484	.02	3
Business	.22	.35	.39	.33	**.39**	.29	**31 325****	**.15**	**39**	27 731	.04	9	25 389	.06	−14	4926	.07	10	7503	.02	−2
Communication	.86	.86	**.91**	.90	.82	.85	35 632	.02	−6	28 119	.02	7	24 752	.07	−19	5045	.05	8	7526	.01	−2
Cooking	.07	.06	**.10**	.08	.05	.07	36 477	.01	−1	28 039	.07	9	26 688	.03	−5	5346	.04	−3	7406	.05	−5
Dating	.18	**.34**	.06	.02	.04	.16	**30 216****	**.20**	**49**	**20 886****	**.36**	**−69**	**26 043***	**.10**	**−11**	5406	.04	2	**6528****	**.27**	**20**
Education	**.44**	.40	.34	.41	.39	.29	35 642	.02	−6	26 928	.07	−16	24 778	.08	19	5183	.03	−5	6778	.10	−16
Entertainment	.67	.71	**.77**	.64	.61	.62	33 437	.07	23	28 177	.02	6	**23 269***	**.12**	**−32**	4836	.08	13	7397	.03	−5
Family	.23	.27	.29	**.37**	.26	.33	35 151	.04	10	27 830	.04	9	24 900	.08	17	4863	.08	−13	7488	.02	−2
Finance	.26	.55	.60	**.63**	.60	.60	**24 012****	**.04**	**95**	26 719	.07	18	26 591	.01	−3	5276	.02	−3	7492	.02	−2
Flirting	.14	**.19**	.03	.02	.02	.13	34 540	.08	16	**24 319****	**.27**	**−41**	26 876	.04	−3	5474	.01	1	**6680****	**.26**	**17**
Games	.82	.80	**.89**	.87	.79	.76	34 501	.33	−15	**24 993***	**.12**	**32**	25 803	.04	−10	5263	.02	−3	**6179***	**.15**	**−26**
Health & fitness	.39	.44	.57	.59	**.60**	.48	33 366	.33	24	**24 993***	**.12**	**32**	26 671	.01	2	5116	.04	6	6611	.11	−19
Hotel	.03	.08	.10	.09	**.12**	.11	**34 782***	**.04**	**14**	28 601	.03	5	26 750	.03	−4	5282	.05	5	7432	.04	4
Instant messaging	.95	.96	.95	**.98**	.88	.93	**28 627****	**.11**	**−61**	28 345	.03	−8	**23 711***	**.12**	**−31**	**4013****	**.20**	**−34**	6884	.08	13
Job search	.09	.15	**.17**	.12	.16	.12	**34 298***	**.10**	**18**	28 428	.03	6	25 759	.07	−13	5286	.05	5	7593	.01	1
Lifestyle	.88	.92	.94	**.98**	.88	.90	**27 442****	**.14**	**69**	26 692	.07	18	25 987	.03	−9	5389	.00	0	6893	.08	−13
Media & video	.34	.36	.36	.34	**.39**	.35	35 296	.19	8	28 818	.00	0	26 161	.03	−7	5043	.05	8	7504	.02	2
Medical	.08	.12	.14	.16	**.23**	.15	34 877	.07	11	28 015	.04	7	26 491	.02	4	5009	.08	9	7586	.01	−1
Music & audio	.75	**.78**	.76	.73	.70	.67	**32 796***	**.09**	**27**	27 469	.04	−12	**23 306***	**.12**	**−32**	4851	.07	13	7332	.03	6
Navigation	.95	.96	.94	**.98**	.88	.91	34 882	.07	13	29 109	.00	1	26 002	.06	11	5141	.07	−8	6942	.11	−13
News & magazines	.18	.27	.29	.27	**.49**	.18	32 836*	.11	**27**	28 443	.02	4	26 149	.03	−7	**3973****	**.23**	**33**	7016	.08	−12
Online banking	.07	.24	.27	**.30**	.25	.22	**30 046****	**.26**	**50**	28 243	.04	8	26 765	.02	4	5262	.04	−6	7171	.06	−9
Period tracking	.15	.11	**.25**	.21	.11	.23	35 196	.06	−11	**25 049****	**.18**	**34**	26 221	.04	−9	4891	.11	−14	7408	.03	5
Personalization	.40	**.50**	.48	.44	.46	.38	**31 971***	**.11**	**34**	27 070	.06	−16	25 705	.04	−11	5113	.04	6	7448	.02	−4
Photo editing	.68	.64	.60	.65	**.68**	.52	34 091	.06	−19	28 134	.03	−9	25 608	.05	14	5236	.04	−6	**6518***	**.12**	**−20**
Photography	.64	.55	.59	**.69**	.56	.63	33 616	.07	−21	27 105	.05	14	24 194	.09	24	4846	.07	−13	6789	.09	−15
Productivity	.63	.71	.72	.75	**.81**	.74	**28 923****	**.18**	**58**	28 576	.01	−2	26 935	.00	0	**4194***	**.16**	**28**	7478	.02	−3
Public transport	**.34**	.18	.19	.08	.04	.13	**30 719****	**.17**	**−45**	28 747	.02	4	**24 070****	**.16**	**−28**	5260	.07	−6	7173	.09	9
Real estate	.04	**.15**	.13	.14	.00	.07	**32 447****	**.20**	**32**	28 436	.04	−6	27 092	.01	1	**4732***	**.18**	**−17**	7193	.08	−8
Restaurant	.08	.18	.16	.14	**.23**	.11	**32 849****	**.16**	**29**	28 882	.01	−3	26 353	.04	−8	4919	.12	13	7519	.02	−2
Shopping	.56	.67	.70	**.77**	.67	.67	**31 524***	**.12**	**37**	**25 041***	**.12**	**32**	24 426	.08	22	5028	.05	−9	**6501***	**.12**	**−20**
Social	.88	.86	.88	**.91**	.82	.80	35 033	.03	−11	**25 004***	**.12**	**−32**	26 360	.02	−5	5194	.03	−5	7443	.02	−4
Sports	.23	.23	.23	.22	**.30**	.16	36 400	.00	0	28 759	.00	1	26 616	.01	−3	4976	.07	10	7183	.07	−8
Taxi finder	.06	**.23**	.14	.17	.12	.09	**30 361****	**.25**	**48**	**26 443***	**.12**	**−23**	26 374	.04	8	5222	.05	−6	7004	.11	−12
Tools	.71	.77	.79	**.80**	.75	.77	**31 194***	**.12**	**40**	27 423	.04	−12	26 353	.02	−5	**4117***	**.17**	**29**	7511	.01	−2
Transportation	**.35**	.34	.31	.19	.21	.28	36 406	.00	0	28 339	.02	−5	**23 490***	**.14**	**−31**	5325	.01	1	6923	.10	13
Travel & local	.32	.49	.52	.45	**.54**	.39	**29 147****	**.19**	**56**	27 084	.06	16	**23 264***	**.13**	**−32**	**4364***	**.15**	**24**	7251	.04	−8
Weather	.25	.38	.41	.47	**.67**	.35	**31 137****	**.15**	**40**	27 516	.05	11	25 789	.04	10	**4044***	**.19**	**31**	6723	.11	−16
Weight & calories	.04	**.12**	.12	.08	.09	.06	**33 840****	**.14**	**21**	29 154	.00	−1	26 311	.06	−8	5455	.01	1	7502	.03	−2
Games: Action	**.27**	.21	.17	.15	.05	.10	33 849	.08	−20	27 833	.05	−9	26 318	.03	−6	4852	.12	−13	7301	.06	−6
Games: Adventure	.14	.15	.18	**.21**	.12	.17	36 202	.01	2	27 716	.05	10	26 446	.02	4	4907	.09	−11	7394	.04	−4
Games: Arcade	**.42**	.32	.34	.24	.18	.15	**31 915***	**.12**	**−35**	28 226	.02	5	**23 776***	**.12**	**−28**	5053	.06	−8	6981	.09	−12
Games: Board	.08	.09	.14	**.16**	.11	.10	35 902	.03	4	27 324	.08	13	26 655	.01	3	5122	.06	−6	7223	.07	−8
Games: Card	.13	.16	.28	.24	**.35**	.20	35 168	.05	10	**25 712***	**.13**	**27**	26 169	.03	−7	**4590***	**.14**	**19**	7367	.04	−5
Games: Casino	.06	.09	.11	.15	**.23**	.09	35 217	.06	9	28 093	.04	7	26 144	.04	7	4898	.10	11	7194	.08	−8
Games: Casual	.46	.46	.53	**.58**	.56	.48	35 966	.01	−4	**25 726***	**.10**	**26**	26 289	.02	6	5039	.05	−8	7021	.07	−11
Games: Educational	.04	.06	.07	**.14**	.07	.10	35 733	.04	5	28 677	.01	2	**25 063***	**.12**	**16**	5035	.08	−8	7404	.04	−4
Games: Music	**.04**	.04	.02	.02	.04	.01	36 429	.00	0	28 269	.06	−5	26 914	.00	0	5304	.04	2	7586	.03	−1
Games: Puzzle	.47	.39	**.51**	.48	.46	.40	34 439	.05	−15	**25 173***	**.12**	**31**	25 727	.04	−11	5147	.03	6	6895	.08	−13
Games: Racing	**.10**	.07	.10	.06	.07	.02	35 272	.05	−9	28 093	.05	7	25 774	.08	−10	5297	.03	2	7410	.06	−4
Games: Role playing	.12	**.13**	.12	.07	.04	.07	36 285	.01	1	28 630	.01	−2	25 608	.08	−12	5211	.06	−4	7597	.01	1
Games: Simulation	**.26**	.21	.26	.19	.09	.13	34 351	.06	−16	27 130	.07	15	24 898	.09	−18	4907	.10	−11	7296	.05	−6
Games: Sports	.10	**.13**	.10	.09	.09	.06	35 368	.05	8	28 154	.04	−6	26 578	.02	−3	5386	.00	0	7440	.04	−4
Games: Strategy	**.25**	.18	.17	.15	.09	.06	33 811	.08	−20	28 494	.02	−3	26 363	.03	−5	5082	.07	−7	**6976***	**.12**	**−12**
Games: Trivia	.28	.28	**.39**	.28	.25	.20	35 975	.01	−4	**25 561***	**.12**	**28**	**23 585***	**.13**	**−29**	5230	.03	−4	7134	.07	−9
Games: Word	.17	.20	.25	.25	.21	**.26**	35 199	.04	9	27 083	.07	15	26 718	.01	−2	5188	.04	−5	7643	.00	0

(continued on next page)

Table 3 (*continued*)

Category	Adoption rate per stage						A vs. B			B vs. C			C vs. D			D vs. E			D vs. F		
	A	B	C	D	E	F	*U*	*r*	*Δ*	*U*	*r*	*Δ*	*U*	*r*	*Δ*	*U*	*R*	*Δ*	*U*	*r*	*Δ*
Family: Action	.10	.09	.12	**.15**	.04	.15	36 167	.01	−2	27 929	.05	8	26 180	.04	7	**4774***	**.14**	**−14**	7585	.01	1
Family: Brain games	.05	.08	.11	.11	**.12**	.09	35 358	.06	8	27 813	.06	9	26 664	.02	−3	5282	.03	3	7511	.03	−2
Family: Create	.05	.03	.04	**.07**	.02	.01	35 700	.05	−6	28 545	.03	3	26 228	.06	6	5128	.09	−6	7233	.11	−7
Family: Education	.08	.11	.09	**.13**	.09	.12	35 129	.06	10	28 328	.03	−5	26 029	.05	8	5191	.05	−5	7615	.01	1
Family: Music video	.03	.04	.01	.06	**.07**	.05	36 097	.03	3	28 195	.08	−6	**25 828***	**.12**	**10**	5303	.03	2	7611	.01	−1
Family: Pretend	.00	.00	.00	**.02**	.00	.02	36 367	.02	1	28 738	.05	−1	**26 400***	**.11**	**5**	5280	.07	−3	7606	.02	1

* Significant at $p < .05$.
** Significant at $p < .001$.

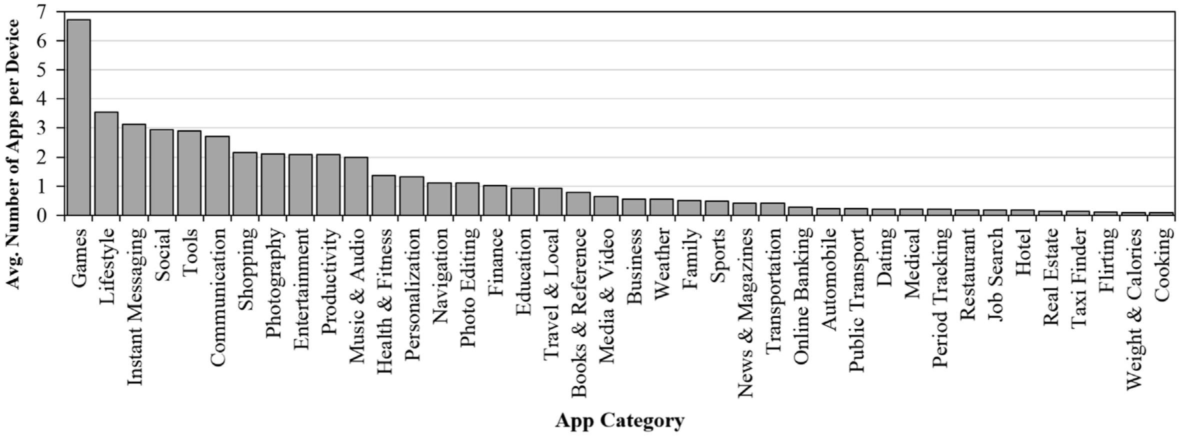

Fig. 6. Average number of apps per device for the 40 most popular app categories ($N = 1435$).

The findings demonstrate that the analysis of app adoption disclose more than just a statement about differences in the life stages. The analysis helps to comprehend the dynamic processes within life cycles as well. Although understanding the root cause of such changes is not the focus of this study, some explanations are provided as follows:

- Transition from A to B
  When teenagers are getting elder and leave the nest for the first time, some big changes in their life are happening: They enter in the job market; they take care on their own finances; they must take care of their daily needs themselves; they need an own apartment; and they start discovering the world (traveling). All these changes are clearly reflected in our results in Fig. 7. The partner search is getting more important as well. We observe a strong increase of dating apps from teenager to single stage. In contrast, instant messaging is widely adopted by teenagers [70]. Our results support this statement and this kind of apps decreases after the teenager stage significantly. Not surprisingly, teenager have the highest adoption rate for educational apps.
- Transition from B to C
  Period trackers on mobile devices are used by women to either get pregnant or to avoid pregnancy. Such apps are popular for couples of childbearing age and we observe a significant increase compared to singles. On the other hand, as soon as singles are getting couples, dating and flirting apps massively decrease. That makes absolutely sense because the partner search is finished for now. The different preferences of transport possibilities is observable as well: Teenager are more interested in public transport apps than older people, because they may have not yet reached the legal driving age or may have not yet the money for an own car. Singles are more interested in taxi apps than couples and for couples, we observe an increase of automobile apps like car vending or car sharing apps.
- Transition from C to D
  The mobility of families with young children is restricted because babies and toddlers have special needs. Parents have a strong preference for short trips, regardless of the travel time available [4]. The limitation in transportation is visible in the lack of apps in travel and transport categories on devices of young families. Moreover, childcare is time-consuming and thus, parents have less time available for entertainment. They reduce social activities (instant messaging, dating) outside of the family as well.
- Transition from D to E
  When children getting older, the app adoption reflects the regained leisure time of the older parents in stage E. Traveling, reading and social activities are getting interesting again. On the other hand, the individual job performance

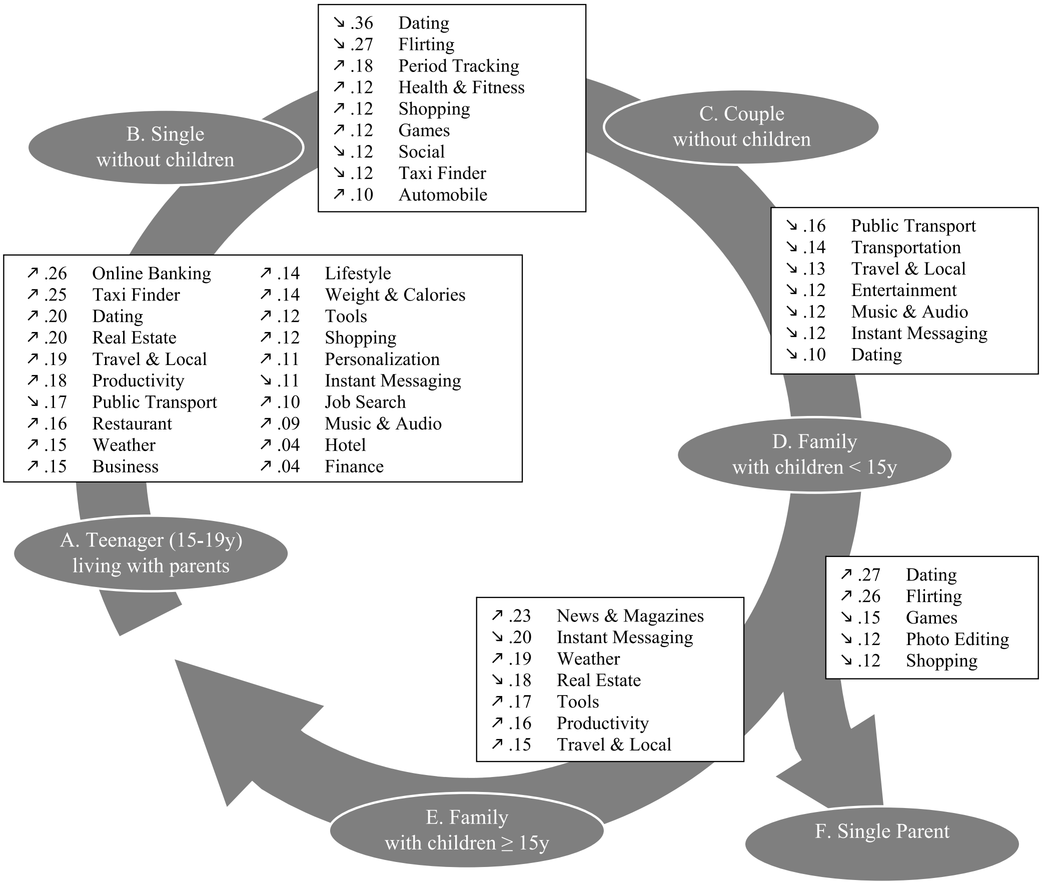

Fig. 7. Life cycle with six life stages displayed as ovals. Rectangular boxes list all significant differences [$p < .05$] of app categories between two neighboring stages. Arrows indicate the trend followed by its effect size. Subcategories are not shown.

is found to decrease from around 50 years of age [71]. We hypothesize that people in this late life stage are trying to compensate the reduction in productivity by using apps of work support categories (productivity, tools). Further investigations are needed to confirm or reject this hypothesis. Further, we observe that medical apps have the highest adoption rate in stage E.

- Transition from D to F

  Time and money of single parents is tight. Limitations with activities of daily living are nearly twice as likely to be reported by divorced younger women and the gap in poverty between divorced and married women has tremendously increased [72]. The adoption behavior of single parents confirms it, as we see a decrease of time-consuming mobile games and costly shopping apps. Meanwhile, finding a new partner seems to be a high priority and the dating and flirting apps massively increase.

The insights demonstrate how informative the installed mobile apps are. For the first time, this kind of dynamic changes is automatically discovered in a selected life cycle. Thus, the first research question is addressed.

4.5. Subcategories

As shown in Fig. 6, games are by far the most popular app genre on mobile devices and it is worth to have a closer look on it. Are there different gaming preferences in the six life stages? The comparisons of the 17 games subcategories between the stages are listed in Table 3. The overall maximum in the adoption of games have couples without children (stage C). In particular, the interest for casual games significantly increases in this stage. Casual games can be played during work breaks or while commuting because their gameplay is extremely simple. Puzzle, trivia, and card games can be seen as casual games. These categories significantly increase as well in stage C. Card games increase in stage E, too and reach a maximum in terms of adoption rate. This observation indicates that older people prefer classic games which are already known from the physical world or from traditional desktop computers. The inverse holds for arcade games: The adoption rate starts at the highest at the beginning of the life cycle and decrease permanently till to the end. As a consequence, the Random Forest model discovers arcade games as a very good predictor for people in life stage F. The results related to Random Forest

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Table 4
Life stage classifier performance ($N = 1435$). Improvement compared to random classification is displayed in brackets.

Life stage	Precision		Recall		Accuracy		Specificity		$LR+$
A	0.765	(+236.0%)	0.263	(+15.4%)	0.814	(+25.5%)	0.976	(+26.4%)	11.0
B	0.444	(+180.2%)	0.174	(+9.6%)	0.834	(+13.8%)	0.959	(+14.0%)	4.2
C	0.338	(+104.5%)	0.306	(+84.6%)	0.786	(+8.6%)	0.882	(+5.6%)	2.6
D	0.294	(+113.2%)	0.333	(+141.7%)	0.798	(+4.7%)	0.872	(+1.2%)	2.6
E	0.250	(+504.2%)	0.167	(+302.8%)	0.945	(+2.6%)	0.978	(+2.1%)	7.7
F	0.222	(+302.8%)	0.167	(+202.1%)	0.922	(+2.9%)	0.966	(+2.2%)	4.9

Table 5
Top-three most powerful indicators in each of the ten Random Forest models.

Life stage	First most frequently used feature	Second most frequently used feature	Third most frequently used feature
A	#Apps in instant messaging	#Apps in finance	#Apps in public transportation
B	#Apps in dating	#Apps in petrol price comparison	#Apps in social media
C	#Apps in flirting	#Apps in dating	#Apps in travel & local
D	#Apps in dating	#Apps in shopping	#Apps in flirting
E	#Apps in weather	#Apps in instant messaging	#Apps in coupon
F	#Apps in photo editing	#Apps in arcade games	#Apps in life style

are presented in the next section. However, young families adopt most educational games. We interpret this as a sign that families perceive mobile devices as a playful learning opportunity for their children (keyword: 'serious games').

The subcategories about family topics were newly introduced in Google Play in 2015. Existent family apps were not automatically tagged by these new subcategories and all app developers have to make up for it themselves. Therefore, at the time of data collection for this study, many family apps were not yet tagged with one of these subcategories. As a result, the adoption rate of our participants is low, i.e. below 16% for all subcategories. Nevertheless, we expect the highest adoption rates of family apps in the two life stages D and E, which cover the families with children. A Mann–Whitney test confirms our hypothesis: Life stages D and E reach together a significant higher adoption rate of family apps than the rest of the stages (union of A, B, C, and F), $U = 10\,4493$, $p = .010$, effect size $r = .08$, and mean rank difference $\Delta = 49$. Table 3 shows additionally the comparison of family subcategories between any two consecutive life stages. The two subcategories 'Music Video' and 'Pretend' are significant higher for families with children (stage D) than for couples without children (stage C). Further, the adoption of 'Action' is significant higher for families with children (stage D) than for families with children older than 14 years (stage E).

4.6. *Accuracy of predicting life stages*

According to the explanations in the data analysis section, we built a predictive model with 70% of the samples and test it with the remaining 30%. In Table 4, we present the results of our performance evaluation. Precision, recall, accuracy, specificity and positive likelihood ratio ($LR+$) are displayed for the six life stages. The results are compared to random model that classifies the participants randomly according to the probability distribution of the survey data. The approach is similar to that of previous studies [38]. Except for $LR+$, each number in a cell in Table 4 represents the prediction performance of our Random Forest model while the number in the parentheses shows the performance improvement compared to the corresponding random model.

Overall, our model performs better compared to a random model in all investigated key figures. Typically, there is a tradeoff between precision, recall and specificity [66,67]. Nevertheless, our model reaches higher precision (up to plus 504.2%) and recall (up to plus 302.8%). In our case, precision and recall are more important because we want to find out users who are really in a specific life stage. In contrast, accuracy shows the overall prediction of people who are in a specific stage or who are not in the stage. As the number of samples that are in a specific stage is much smaller than the rest, a random model can thus always reach a high accuracy by addressing the majority. However, it does not provide much information because in reality we mainly care about predicting people who are in a specific life stage. It is similar for specificity. Therefore, our models perform well as the precision and recall of all stages are strongly improved.

The good result is also reflected in the high positive likelihood ratio, a well-established key figure in medical diagnostics. A ratio greater than 1 means that people who are positive classified have an increase probability that they are currently in the specific life stage. Stage A with a ratio larger than 10 has even a "large and often conclusive increase in the likelihood", according to Riddle and Stratford [73].

To sum up, it is possible to target people with a higher accuracy, higher precision and higher specificity compared to our random model. Furthermore, statements about estimations of individuals' life events are better than random in general. In addition, we present the top-three most powerful indicators in each of the ten Random Forest models in Table 5. Number of social apps like dating, social media, instant messaging and flirting are most widely used to distinguish different life stages. Thus, the second research question is answered.

5. Discussion, limitations and future work

5.1. Findings and managerial implications

In the previous section, we provide a novel method to predict life stages. The method is automatable, scalable, language-independent, easy to implement, and applicable in real-time. It enables companies to do customer segmentations neither with big investments nor with deep technical knowledge. The list of installed apps on a specific device is freely accessible for each app installed on that device and thus, also for the app provider. It allows them to provide personalized content, offers, products, and services to their customers. Collaboration-based recommender systems can be improved as well as new potential customers can be identified. More effective personalized promotion can be conducted [74] and a big picture of the customers over a long period time can be sketched. Finally, the cold-start problem can be overcome because the list of apps is available from the beginning.

We investigated the correlations between installed apps and life stages. We found that people at different life stages install significantly different mobile apps. Encouraged by the findings, we generated machine-learning models to predict each smartphone user's current life stage based on her installed apps. On average, our predictive model performs 241.0%, 148.2%, 6.5%, and 5.0% better than random model in terms of precision, recall, accuracy, and specificity. The highest accuracy rates with 0.834 and 0.814 are reached by the estimation of 'teenager, living with the parents' and 'single without children'. The overall good results indicate that our method is valuable for the automatic estimation of life stages. The method joins the trend towards customer data analysis at the interface between the online and offline world. It enables new marketing and business opportunities in most existing business fields.

However, using personal customer data might trigger privacy concerns. In the present study, we proved that the collection of installed apps can be used to predict life stages and to create user profiles. Therefore, such data should be considered as personal data which is sensitive related to privacy concerns. Customers are not willing to share their personal data in any cases and want to be asked for explicit consent in advance. Resisting the sore temptation of gathering, storing and using personal data without consent and reward can be hard for companies in an environment with great innovation pressure and competition. Our method can be used without explicit user permission, saying the data gathering process can be done hidden from the user. In order to counteract undesirable behavior, there are reinforced policies for app provider, released by app markets like Google Play. Today, using our method without asking for explicit consent would violate its developer program policies and may lead to suspension of the app from the app market. We call for a responsible behavior as we did in this work. The positive experience with our app showed that most users are willing to share their data if they are asked in advance, get the purpose well-explained, and receive a suitable incentive.

5.2. Limitations and future work

There are some limitations on this paper, which provides opportunities for future research. First, there is a selection bias because most participants of the study were Facebook users. In particular, the distribution of gender was not balanced. 75% of the samples were female. Previous research showed that women are more likely to heavily use Facebook and the like [75,76]. We expect different app installation behavior between women and men. In future research, we intend to address the differences by building models for both genders separately and thus, we except more accurate prediction results. Furthermore, one might think that Facebook users have a different app adoption behavior compared to non-Facebook users. However, a recent user study [15] could not find significant differences in personality traits (which are connected to different app adoption behavior [77]) of Facebook users, and the massive proliferation of Facebook in the investigated countries reduces the possibility for a selection bias as well. Second, we used the app categories out of the box. Although our predictions are already good, we expect an improvement by optimizing the selection of these categories. It can be easily done automatically by parsing the app description on app markets and then deriving categories related to life stages. Third, we refrain from other available data on mobile devices such as the installation time and update time or the list of currently running apps. The usage helps to identify the moment of stage change or to sort unused apps out. In future work, we will include this additional data in our prediction model. Metadata from the app market platforms could enhance the results as well. For instance, the price could be an interesting factor because the purchasing power in life stages differs.

6. Conclusion

The contribution of the present work is two-fold. First, based on a large user study, insights of mobile app adoption in different life stages are provided. Second, a method to automatically predict life stages based on data from mobile devices is proposed and evaluated. Precision, recall, accuracy, and specificity are significant better than random in all investigated life stages. The method promises high potential with low investment costs for companies who provide an app on the market. From customers' perspective, they can benefit from personalized products and services without answering painful and time-consuming questionnaires and without revealing highly sensitive data like email content or network traffic. Furthermore, the life cycle research is no longer dependent on historic data. Researcher are now able to observe life stages in real-time and in a non-intrusive way.

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Appendix. App categories

Two methods for app categorization are described and used in this article, namely 'developer-tagged' and 'description-based'. The lists of all categories are displayed below.

A.1. Developer-tagged

Main categories				
Books & reference	Family	Lifestyle	Personalization	Sports
Business	Finance	Media & video	Photography	Tools
Comics	Games	Medical	Productivity	Transportation
Communication	Health & fitness	Music & audio	Shopping	Travel & local
Education	Libraries & demo	News & magazines	Social	Weather
Entertainment				
Subcategories				
Family: Action	Family: Pretend	Games: Card	Games: Puzzle	Games: Sports
Family: Brain games	Games: Action	Games: Casino	Games: Racing	Games: Strategy
Family: Create	Games: Adventure	Games: Casual	Games: Role playing	Games: Trivia
Family: Education	Games: Arcade	Games: Educational	Games: Simulation	Games: Word
Family: Music video	Games: Board	Games: Music		

A.2. Description-based

Categories				
Alarm clock	Coupon	Hearth rate monitor	Parenting	Skiing
Alcohol tracking	Cricket	Hotel	Period tracking	Smart watches
Art	Currency converter	Instant messaging	Pet	Soccer
Automobile	Cycling	Job search	Petrol price comparison	Sports entertainment
Baking	Dancing	Jokes	Photo editing	Stock market
Baseball	Dating	Language learning	Poker	Supermarket
Blood pressure tracking	Delivery tracking	Laws	Pregnancy	Tattoo
Body building	Dieting	Luxury shopping	Public transport	Taxi Finder
Business conference	Eye test	Manga	Quit smoking	Television
Calculator	Fashion	Massage	Radio	Tennis
Casino	First aid	Meditation	Real estate	To-do list
Celebrity	Fishing	Money budget management	Relaxation	Tutorials
Chess	Flight search & tracking	Mortgage calculator	Restaurant	University
Cinema	Flirting	Motorcycle	Romance	Wedding
Climbing	Gardening	Navigation	Running trackers	Weight & calories
Cocktails	Golf	Nightlife	Sex positions	Wine
Concert	Hairstyle	Online banking	Shopping list	Yoga
Calculator				

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