Towards Predicting Hexad User Types from Smartphone Data

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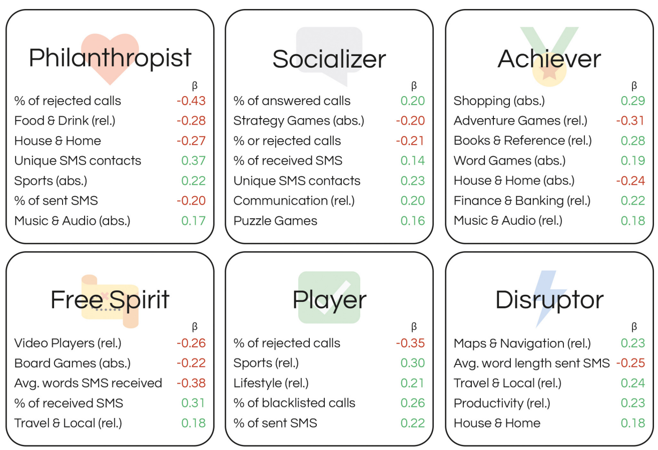

Figure 1: Regression models, predicting user types from smartphone data. β = standardized regression coefficient

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Abstract
Tailoring gamified systems has been shown to be appreciated and more effective than "one-size-fits-all" systems. A promising approach is using the Hexad user types model. However, obtaining the Hexad user type requires users to fill out a questionnaire, preventing an automated adaptation. Since smartphone data was shown to be linked to personality traits, which in turn were shown to be linked to the Hexad user types, we explore to what extent it can be used to predict the score of each user type. In our study (N=122) we found regression models, indicating that using smartphone data to predict user types is promising and may allow to tailor gamified systems without explicit user interaction.

Author Keywords
Gamification; Personalization; Hexad

CCS Concepts
•**Human-centered computing** → *User models;*

Introduction
Gamification, using game elements in non-game contexts [7], has been successfully used to motivate users to reach their goals or enhance their experience [9, 10]. While in general most gamified systems have been shown to elicit positive outcomes when adopting a "one-size-fits-all" approach [21], some studies also reported mixed or even negative re-

Philanthropists ("PH")
Like to bear responsibility and share knowledge.

Driven by: **Purpose**.

Game elements: Collecting, Gifting, Knowledge Sharing

Socializers ("SO")
Socially-minded, interested in interacting with others.

Driven by: **Relatedness**.

Game elements: Networks, Comparison, Competition

Free Spirits ("FS")
Want to express themselves.

Driven by: **Autonomy**.

Game elements: Exploration, Unlockable Content

Achievers ("AC")
Want to overcome difficult challenges.

Driven by: **Competence**.

Game elements: Challenges, Quests, Badges, Progression

Players ("PL")
Will do their best to earn extrinsic rewards.

Driven by: **Rewards**.

Game elements: Points, Badges, Leaderboards

Disruptors ("DI")
Want to test the boundaries of a system.

Driven by: **Change**.

Game elements: Innovation Platforms, Votings, Creativity

Sidebar 1: Hexad User Types Descriptions

sults [9, 21]. This might be explainable by research suggesting that the motivational impact of game elements differs substantially across users [24]. This is why understanding how to individualize gamified systems has gained attention as a topic for research. To tailor and inform the design of gamified systems, the Hexad user types model [14] was developed. Tondello et al. [24] created a survey for this user type model and showed its validity [23]. Moreover, correlations between the Hexad user types and game elements have been shown [24], which allow for tailoring gamified systems based on user types. However, users are required to fill out a questionnaire beforehand, which prevents tailoring gamified systems without explicit user interaction.

To counter this, we investigate the potential of using smartphone data (installed applications, phone calls, SMS messages, contacts) to predict user types. We developed an Android app gathering smartphone data and obtaining Hexad user types, which was used in a user study (N=122). We found regression models for each user type, indicating that deriving user types on the basis of smartphone data is promising (see Figure 1). Our results could be used to tailor gamified systems without requiring explicit user input.

Related Work

Research has been conducted on how gamified systems can be individualized. For instance, Jia et al. [10] investigated the relationships among personality traits and perceived preferences for several motivational affordances used in gamification. They found multiple significant correlations which may be helpful to target certain populations based on personality. Besides personality, studies also showed that preferences and play motives change with increasing age [1, 4] and that gender might influence the perception of some motivational affordances [17].

Moreover, research has been carried out to examine whether player type models can be used to tailor gamfied systems. The Hexad user types model [14] is a model that is specifically developed for gamified systems [16]. It consists of six user types differing in the degree to which they are driven by their needs for autonomy, relatedness, competence and purpose (as defined by the Self-Determination Theory [20]). Tondello et al. [23, 24] developed a validated questionnaire to derive a users' Hexad type. It is important to note that users do not belong to one specific class but rather that the overall distribution of the scores of each user type needs to be considered. A short description of user types and selected suitable game elements (based on [14, 24]) can be found in Sidebar 1. Tondello et al. [24] also found several significant correlations between Hexad user types and the perception of game elements. Also, Orji et al. [16] showed that the Hexad user types play a significant role in the perception of several motivational affordances. In addition, correlations between the Hexad user types and the Big-5 personality traits have been shown [24]. Furthermore, Altmeyer et al. [2] found that combining Hexad user types and behavior change intentions may help to personalize game elements within a fitness context.

Exploring the idea of predicting Hexad user types from smartphone data is inspired by previous work researching to what extent personality traits explain smartphone usage and vice-versa. Phillips et al. [18] found that personality influences the usage time of mobile phones. Also, Lane et al. [11] found that personality traits explain mobile phone application use. Finally, using smartphone apps to predict user traits was researched by Seneviratne et al. [22]. The authors applied machine learning and were able to achieve a high precision using the list of installed apps and information such as app categories from the Google Play Store.

Participants

122 participants took part (gender: 41.8% female; age 27 on average). 63 participants were recruited through mailing lists and social media. 59 were recruited through Amazon Mechanical Turk ("AMT"). On AMT, we restricted the selection to US Turkers having an Android smartphone as their primary device. AMT Workers received $2 as compensation (the study took 10 minutes). The user types score distribution was found to be almost the same as in [24]:

	Mean	SD
PH	23.16	3.89
SO	19.76	5.40
FS	22.63	3.11
AC	21.94	3.86
PL	21.36	4.52
DI	14.81	5.07
OP	7.75	1.94
CO	7.36	2.02
EX	5.91	2.41
AG	6.80	2.06
NE	5.34	2.28

Mean & standard deviation (SD) of the Hexad user types and the Big 5. OP=Openness, CO=Conscientiousness, EX=Extraversion, AG=Agreeableness, NE=Neuroticism.

Sidebar 2: Information about participants of the study

Summing up, research has shown that individualizing gamified systems is appreciated and more effective than "one-size-fits-all" approaches [12]. Moreover, several factors (e.g. age [1, 4], gender [17], personality [10, 15], player types [16, 24]) were identified, allowing tailoring of gamified systems. A promising approach is using the Hexad user types model, as it was specifically developed for gamified systems [16]. Additionally, it is the only model for which correlations to the perception of individual gamification elements were shown [24]. However, using this model requires to fill out questionnaires, which implies explicit user interaction. Therefore, we explore to what extent smartphone data can be used to predict the score of each Hexad user type. This idea is inspired by the aforementioned studies, showing that smartphone data is linked to personality traits [11, 18, 22] and that personality traits correlate with Hexad user types [24].

Research Prototype

We developed a smartphone app for the user study. While filling out the survey, the app gathers the following smartphone data: **Installed applications** (Package name, application name, install date, category of the app in the Google Play Store), **Phone calls** (Average call duration, percentage distribution of types (initiated, answered, missed, rejected, blacklisted)), **Short Message Service ("SMS") messages** (Average number of words for sent and received messages, average word length for sent and received messages, percentage distribution of sent and received messages), **Contacts** (The number of unique message and call contacts). Attributes related to **communication data** (phone calls, SMS messages, contacts) were inspired by Chittaranjan et al. [5], who found these attributes to be related to the Big 5 personality traits. Similarly, installed applications were used because Lane et al. [11] and Seneviratne et al. [22] found these to be related to personality traits, too.

Evaluation

The study was designed to investigate the potential of using smartphone data to predict the score of each of the six Hexad user types. Participants were asked to install our smartphone app from the Play Store. While the app gathered the above-mentioned smartphone data, they filled out a survey covering demographical data, Hexad user types [24] and the Big Five Inventory (BFI-10 [19]). The study was approved by our Ethical Review Board[1].

Descriptive Data

Information about participants, the Big-5 and the Hexad user types distribution can be found in Sidebar 2. Sidebar 3 provides a descriptive overview of the smartphone data we have gathered.

Predicting Hexad User Types

We use stepwise multiple regressions to find potential models predicting the score for each user type. In stepwise multiple regression, a combination of forward selection and backward elimination is used. It should be noted that this method was chosen since we did not have specific assumptions about which predictors are most relevant for each user type and because our goal was in the first place to explore the potential and feasibility of using smartphone data to infer user types implicitly. To reduce Type 1 errors, which might occur due to the multiple iterations performed by the stepwise method, the Benjamini-Hochberg false discovery rate [3] was used. As predictors, the absolute number of installed apps for each Play Store category and participant (see Sidebar 4), the relative number of installed apps per participant for each Play Store category (the absolute number divided by the total number of installed apps) and communication data (phone calls, SMS messages and contacts) were entered into each model. We decided to include

[1] https://erb.cs.uni-saarland.de/, last accessed August 9, 2019

Smartphone Data

The average age of participants' smartphones was 506.11 days. Participants had 73.11 apps installed. Furthermore, most of the installed apps belong to the "Tools" (20.63%) , "Productivity" (12.99%) and "Communications & Messaging" (11.29%) categories. The most frequently installed apps were YouTube (99.18%), Google Maps (96.72%), GMail (94.26%), Google Hangouts (71.31%), Facebook (51.64%), WhatsApp (50.82%), Facebook Messenger (50.00%) and Instagram (43.44%).

Participants had 65.43 call and 30.07 message contacts. An average call lasted 3.33 minutes . 24.97% were answered, 21.10% were missed, 2.94% were rejected, 50.10% were outgoing, and 0.41% were blacklisted. Moreover, 25.66% of SMS were sent while 74.34% were received. On average, received SMS contained 15.74 words, while sent SMS contained 8.80 words.

Sidebar 3: Smartphone data of participants

the absolute and the relative amount of apps per category to reflect both personal preferences and overall app distribution. For all multiple regression analysis, the assumptions of normality, linearity, homoscedasticity and independent errors were met and indicators of multicollinearity were within acceptable limits (for all tolerance > 0.6; VIF < 2) [8].

Philanthropists

Predictor	b	SE B	β	$p_{adj.}$
% of rejected calls	-0.16	0.03	-0.43	0.000
Food & Drink (rel.)	-1.27	0.33	-0.28	0.000
House & Home (rel.)	-2.47	0.66	-0.27	0.000
Unique SMS contacts	0.04	0.01	0.37	0.000
Sports (abs.)	0.62	0.21	0.22	0.004
% of sent SMS	-0.04	0.16	-0.20	0.021
Music & Audio (abs.)	0.34	0.15	0.17	0.021

Table 4: Philanthropists: beta values, standard error (SE), standardized beta values (β) and adjusted p-values

We found a significant regression equation (R=.67, R^2 adjusted=.41, F(7,114)=13.03, p<.000, see Table 4). The negative influence of the percentage share of rejected calls and the positive influence of the number of SMS contacts might be well explained by the basic social attitude of the Philanthropist. Taking into account that Philanthropists are socially-minded but not primarily interested in initiating social interaction, the negative influence of the percentage of sent SMS messages also seems reasonable. Furthermore, the positive influence of "Sports" apps relates well to the preference of Philanthropists for administrative roles, as many fantasy team management apps belong to this category. However, the influence of "Music & Audio", "Food & Drink" and "House & Home" apps is not directly explainable by the definition and motivational factors of the Philanthrophist user type.

Predictor	b	SE B	β	$p_{adj.}$
% of answered calls	0.08	0.03	0.20	0.032
Strategy Games (abs.)	-1.52	0.63	-0.20	0.032
% of rejected calls	-0.11	0.04	-0.21	0.032
% of received SMS	0.02	0.01	0.14	0.076
Unique SMS contacts	0.03	0.01	0.23	0.032
Communication (rel.)	0.27	0.12	0.20	0.032
Puzzle Games (rel.)	0.40	0.20	0.16	0.057

Table 5: Socializers: beta values, standard error (SE), standardized beta values (β) and adjusted p-values

Socializers

A significant regression equation (R=.55, R^2 adjusted=.26, F(7,114)=7.07, p<.000, see Table 5) was found. Given that relatedness is the most important motivational factor, the positive impact of answered calls, received SMS messages, unique SMS contacts and the relative number of communication apps together with the negative influence of rejected calls is not surprising and fits the motivational aspects of the Socializer user type very well. However, the potential reasons for why puzzle games positively and strategy games negatively influence the score are not so obvious and do not directly fit the characteristics of this user type.

Free Spirits

Predictor	b	SE B	β	$p_{adj.}$
Video Players (rel.)	-0.42	0.14	-0.26	0.005
Board Games (abs.)	-0.93	0.36	-0.22	0.014
Avg. words SMS received	-0.12	0.03	-0.38	0.000
% of received SMS	0.03	0.01	0.31	0.005
Travel & Local (rel.)	0.28	0.13	0.18	0.039

Table 6: Free-Spirits: beta values, standard error (SE), standardized beta values (β) and adjusted p-values

We found a regression model consisting of five predictors (R=.48, R^2 adjusted=.19, F(5,116)=6.80, p<.000, see Ta-

Play Store Categories

Books & Reference
Business
Communications
Education
Entertainment
Finance
Food & Drink
Health & Fitness
House & Home
Lifestyle
Maps & Navigation
Music & Audio
News
Personalization
Photography
Productivity
Shopping
Social
Sports
Tools
Travel & Local
Video Players
Weather
Action Games
Adventure Games
Arcade Games
Board Games
Card Games
Casual Games
Puzzle Games
Role Playing Games
Simulation Games
Strategy Games
Trivia Games
Word Games

Sidebar 4: A list of categories from the Google Play Store

ble 6). While the preference for "Travel & Local" apps might be well explainable by the need to explore and discover, which is likely satisfied when traveling, the negative impact of board games might be related to the fact that board games usually have a fixed rule-set and thus potentially compromise the need for autonomy. However, why Free Spirits seem to receive many SMS messages with a low number of average words and why the relative amount of apps in the "Video Players" category negatively influence the score on the Free Spirits scale is not directly explained by the characteristics of this user type.

Achievers

Predictor	b	SE B	β	$p_{adj.}$
Shopping (abs.)	0.47	0.14	0.29	0.002
Adventure Games (rel.)	-1.55	0.42	-0.31	0.000
Books & Reference (rel.)	0.53	0.16	0.28	0.002
Word Games (abs.)	1.08	0.48	0.19	0.032
House & Home (abs.)	-2.56	0.91	-0.24	0.009
Finance (rel.)	0.32	0.13	0.22	0.025
Music & Audio (rel.)	0.36	0.17	0.18	0.034

Table 7: Achievers: beta values, standard error (SE), standardized beta values (β) and adjusted p-values

Seven predictors (see Table 7) were found (R=.51, R^2 adjusted=.22, F(7,114)=5.83, p<.000). The "Shopping", "Books & Reference" and "Finance" category have in common that apps in this category often convey competence. Also, "Word Games" (e.g. "Scrabble") build on competence and often require players to overcome challenges demanding mental abilities, which relates well to the characteristics of Achievers. However, the negative influence of "Adventure Games" and "House & Home" is not directly explainable by the specific needs of Achievers.

Predictor	b	SE B	β	$p_{adj.}$
% of rejected calls	-0.15	0.04	-0.35	0.000
Sports (rel.)	0.93	0.25	0.30	0.000
Lifestyle (rel.)	0.42	0.18	0.21	0.018
% of blacklisted calls	0.61	0.19	0.26	0.003
% of sent SMS	0.05	0.02	0.22	0.018

Table 8: Players: beta values, standard error (SE), standardized beta values (β) and the adjusted p-value

Players

A significant regression equation was found (R=.51, R^2 adjusted=.26, F(5,116)=8.11, p<.000, see Table 8). While the positive influence of blacklisted calls might be explainable by the tendency of players to take care of their own needs, the negative influence of rejected calls and the positive impact of sent SMS messages seem contrary. However, the strong positive correlation between the Player and Socializer, which was shown in [24], might explain these findings. Also, the positive impact of "Sports" apps might be explainable by the strong correlation between the Player and the Achiever [24], as this predictor was also found for the Achiever user type. However, no clear potential explanation can be given for the "Lifestyle" category.

Disruptors

Predictor	b	SE B	β	$p_{adj.}$
Maps & Navigation (rel.)	0.76	0.29	0.23	0.011
Avg. word length sent SMS	-0.52	0.17	-0.25	0.011
Travel & Local (rel.)	0.62	0.22	0.24	0.011
Productivity (rel.)	0.26	0.10	0.23	0.011
House & Home (abs.)	2.54	1.20	0.18	0.036

Table 9: Disruptors: beta values, standard error (SE), standardized beta values (β) and adjusted p-values

A regression model was found (R=.46, R^2 adjusted=.18, F(5,116)=6.29, p<.000, see Table 9). Considering that autonomy and creativity are also important motivators for Disruptors [24], the positive influence of “Maps & Navigation” and “Travel & Local” categories is not surprising as they both relate well to the need to explore and discover. The positive influence of the “House & Home” category also relates well to the importance of creativity as this category deals with apps about interior decoration and home improvement. However, the positive influence of the “Productivity” category and the negative impact of the average word length in sent SMS messages are not directly explainable via the main motivations of Disruptors.

Discussion

Our goal was to explore whether smartphone data can be used to infer Hexad user type scores in order to tailor gamified systems implicitly, i.e. without the necessity of filling out questionnaires. Summing up, we found regression equations that can be used to predict the score of each of the six user types of the Hexad model. The models explain between 18% and 41% of the variance, thus having medium [6] to large [6] effect sizes. This suggests that inferring user types from smartphone data is promising to be further investigated as it could be used to tailor gamified systems automatically. This finding is relevant for gamified smartphone apps that could adapt their game elements without the need for explicit user input and thus could motivate their users more effectively. Our descriptive findings are in line with previous research: The user type distribution is nearly exactly the same as the distribution in the paper by Tondello et al. [24]. Furthermore, participants had a similar app category distribution as in [22]. Even though we were not able to explain all predictors found (potentially because of age-related or cultural differences), overall the most important motivational factors of each user type were reflected in the corresponding model. On a meta-level, this suggests that preferences for smartphone app categories and smartphone communication behavior could explain the personal importance of motivational needs [20], which might be a relevant result also outside of the gamification domain.

Limitations

Although using stepwise regression is a suitable method for exploratory model building [8], the method is prone to model selection bias, resulting from including explanatory variables because of significant F statistics, which might in reality have no (or very weak) relationships to the response variable (“Freedman’s paradox”) [13]. This can lead to overestimations of the importance of certain predictors, which should be considered. As a consequence, the models we have found are not necessarily the only possible models, nor the best ones. Also, it should be considered that Play Store categories are assigned by the publishers of smartphone applications. Even though they should be interested in assigning a suitable category, a certain amount of fuzziness is unavoidable.

Conclusion and Future Work

To allow inferring Hexad user types to tailor gamified systems automatically, we explored whether smartphone data could be used to predict Hexad user types. Indeed, our results reveal regression models for each user type, indicating that investigating relationships between smartphone data and preferences for gamification elements is promising.

In future work, validating our models with a different sample is a crucial next step. Also, more participants should be recruited to investigate more fine-grained factors (such as single apps instead of categories). When considering a higher amount of participants and features, more sophisticated machine learning approaches could be evaluated to enhance the prediction. In addition, privacy-related aspects should be carefully considered and investigated.

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