Towards Predicting Hexad User Types from Mobile Banking Data
An Expert Consensus Study

ROBBE KIMPEN, Department of Computer Science, KU Leuven, Belgium
ROBIN DE CROON, Department of Computer Science, KU Leuven, Belgium
VERO VANDEN ABEELE, Department of Computer Science, KU Leuven, Belgium
KATRIEN VERBERT, Department of Computer Science, KU Leuven, Belgium

The Hexad user types model is often used in the gamification community to tailor gamified systems. However, most often, it requires users to fill out a questionnaire, preventing an automated adaptation of the interactive system. For this reason, we explored the potential of using mobile banking data to automate the profiling of Hexad user types. In our study, we conducted an expert consensus study to research whether a group of experts (N=11) in the field of gamification and banking perceive there is a relation between the Hexad user types and banking data. The results show that experts find this relation present, indicating that automating the calculation of Hexad user types from banking data could be feasible.

CCS Concepts: • **Human-centered computing → User models**; **Empirical studies in HCI**.

Additional Key Words and Phrases: Gamification; Personalization; Hexad; Prediction

ACM Reference Format:

Robbe Kimpen, Robin De Croon, Vero Vanden Abeele, and Katrien Verbert. 2021. Towards Predicting Hexad User Types from Mobile Banking Data An Expert Consensus Study. In *Extended Abstracts of the 2021 Annual Symposium on Computer-Human Interaction in Play (CHI PLAY '21), October 18–21, 2021, Virtual Event, Austria.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3450337.3483486

1 INTRODUCTION

Gamification, often described as "*the use of game elements in non-game contexts,*" [10] is used to increase user engagement, activity, and enjoyment. However, the gamification research community is increasingly questioning the effectiveness of *one-size-fits-all* approaches [27]. More and more studies are suggesting gamified systems are likely to result in higher engagement, and improve desired outcomes, when they take end users' personal characteristics into account [1, 26]. Examples of personal characteristics are age [29] or gender [30]. Besides these personal characteristics, user typologies are specifically developed for tailoring gamified systems, like the commonly used Hexad model [5, 14, 23].

A major disadvantage of relying on user typologies to tailor interactive systems is that they often require explicit user input; most user typology models require users to manually fill out lengthy questionnaires [39]. Moreover, recent research also highlights that user types are highly dynamic [7] and depending on platform and context [40]. To mitigate these shortcomings, we explore the potential of using mobile banking data retrieved through a third party banking app to automatically, and continuously, derive Hexad user types. After all, banking data can provide an exhaustive and up-to-date overview of a person's personality [11]. In this work-in-progress paper, we outline an expert consensus study based on Gielis et al. [15] where 11 gamification and banking experts mapped the six Hexad user types upon bank transaction categories and interaction patterns with a mobile banking app. Results show that five out of six Hexad user types could potentially be derived based on a moderate to strong relationship with a user's mobile banking data.

The main contribution of this paper is an exploration of the feasibility of automatically deriving Hexad user types based on mobile banking data. This can be useful, for example, when trying to support users in making smarter financial decisions through tailored motivational messages (e.g., save money on lottery). Nasirzadeh and Fathian [28] already highlighted the potential of personalized gamification in the domain of banking by developing a new 38-item survey. However, to the best of our knowledge, these is currently no similar previous research available that tries to map Hexad user types onto mobile banking data.

2 RELATED WORK

We have conducted an expert consensus study to explore the feasibility of automatically deriving Hexad user types based on mobile banking data. We therefore first explain the Hexad gamification user type model. Second, we provide examples of previous research towards alternative methods to surveys to assess user type models.

2.1 The Hexad user type model

In 2013, Andrzej Marczewski developed the Hexad gamification user type model [5, 23] for gamified systems. Currently, it has become one of the most used models to determine gamification user typologies [2, 4]. The Hexad model consists of six user types and their associated motivations based on [37] differing in the degree to which they are driven by their needs for autonomy, competence, purpose and relatedness (as defined by the Self-Determination Theory (SDT) [32]):

- **Philanthropists** are motivated by purpose, i.e., helping others without expecting anything in return.
- **Socialisers** are motivated by relatedness, i.e., being involved with others, having social connections.
- **Free Spirits** are motivated by autonomy, i.e., driven by exploration.
- **Achievers** are motivated by competence, i.e., feeling skilled enough to accomplish tasks.
- **Players** are motivated by extrinsic rewards, i.e., rewards that are independent of the activity.
- **Disruptors** are motivated by change, i.e., disrupting the system and testing its boundaries.

Tondello et al. were the first to show correlations between the Hexad user types and the preference for gamification elements [39]. This was an important step to allow for tailored gamified systems. To determine the Hexad user types, they developed and evaluated a questionnaire of 24 questions to classify users' preferences towards the six different user types. Their questionnaire has become the de facto model used in tailored gamification studies [3, 25, 38], and even has validated translations like [36]. According to Hallifax et al. [19], the Hexad model is the most suitable typology for tailoring gamified systems. However, previous research has also shown that completing an online survey can be perceived as dull, resulting in negative respondent behavior such as random responding, speeding, lack of attention or premature termination [16, 21, 31]. All this leads to the sub-optimal situation, where using a questionnaire to assess Hexad user types may not be a suitable option outside of a research context. There is thus a need for automating the process of assessing Hexad user types.

2.2 Alternative methods to calculate user type models

Earlier research has already focused on deriving user types based on social media, interaction, and log data. For example, Farnadi et al. [12] used machine learning techniques to recognize the Five-Factor Model of Facebook users. They used social network properties, the text of their status updates and their frequencies and time of posting. Altmeyer et al. [4] developed a gameful application named "Cloud Clicker" to predict Hexad user types. They found that the interaction with the game elements of "Cloud Clicker" and the validated Hexad scores of the application's users are correlated for all user types and share a substantial amount of variance. However, in "Cloud Clicker", gamification elements already needed to be integrated in the application. Closest to our work, Altmeyer et al. [2] explored to what extent smartphone data (e.g., % of answered calls, unique SMS contacts, which type of apps are installed) can be used to predict Hexad user types. They found regression models that can be used to predict the score of each of the six Hexad user types. The models explain between 18% and 41% of the variance, thus having medium to large effect sizes [8]. This suggests that using smartphone data to predict Hexad user types is promising.

3 METHODOLOGY

3.1 Mobile Banking Data

Mobile banking data can provide an exhaustive and up-to-date overview of a person's personality [11], we, therefore, used the freely-available app Cake [6], which assigns unique categories (which are listed in Table 1) to each bank transaction to provide their users with an overview of how much they spend at each category. These categories, in combination with possible interaction patterns with the app (which are listed in Table 2), were used in this research to conduct an expert consensus study to find out if they potentially could be used to predict Hexad user types.

Table 1. Categories available in the "Cake" banking app. The first column represents the main category while the second column represents the sub-categories that are given to each banking transaction. There is also a category named "other" available if non of the categories from the table would be suited for the transaction.

Main category	Subcategory
Bank services	ATM fee; Bank costs; Credit card fee; Loans; and Interests
Cash	Cash
Payment services	Credit card payment
Children	Babysitting and daycare; Children pocket money; Children recreational activities; Children products; Children clothing; Children toys; and Alimony
Communication	Internet; Phone; and TV
Fines	Traffic fines
Food and drinks	Alcohol; Coffee shops; Bakeries; Groceries; Fast food; Restaurant and bars; and Butcher
Health and beauty	Fitness; Health and beauty products; Spa and massages; and Hair and beauty services
Healthcare	Doctors and hospitals; Dentist; Glasses and Optometrist; Health supplies; Pharmacy and drugs; and Weight loss services
Home	Construction; Electrician appliances; Electricity; Electricity and gas; Furniture; Garden; Gas; Home cleaning and care; Home improvement and repairs; Home security; Interior; Laundry; Mortgage; Rent; Storage; and Water
Income	Cashback; Child support; Inheritance; Paycheck; Retirement income; Rental income; Social security income; and Payback
Information and education	Education fees; and School and book fees
Insurance	Car insurance; Home insurance; and Personal and family insurance
Mobility	Car; Carwash; Car maintenance; Cycling; Gas and fuel; Parking; Public transport; Shared mobility; and Taxi
Pets	Pet supplies
Savings and investments	Emergency fund; Kids savings; Regular savings; Investments; and Retirement savings
Shopping and services	Charity; Clothing and accessories; Electronics, computers and software; Jewelry; Media, music and games; Newspapers and magazines; Books; Parties and celebrations; Photography; Postage and deliveries; Sport equipment; Stationary; and Office supplies and paper
Tax	Municipality taks; and Income taks
Travel and leisure	Arts and crafts; Associations; Entertainment and night-life; Events; Flights; Hotels and campsites; Leisure activities; Lotteries and bets; Movies; Music and Instruments; and Sport activities

Table 2. Table with the interaction patterns from the "Cake" banking app.

Actions available inside the Cake app:
People change the category of a transaction.
People change the location of a transaction.
People shop at a partner of Cake from where they get a special reward from inside the Cake app.
People share their received rewards from inside the app on social media.
People recommend Cake to a friend/ family member/... and receive one euro from the "member gets member" program of Cake.
People give their bank account in the Cake app a custom name.
People open above avarage the Cake app.

3.2 Expert consensus study

The objective of this study is to research the potential of automatically deriving Hexad user types based on mobile banking data. We therefore asked both gamification and financial experts to rate the relation between the six Hexad user types to each bank transaction category (which are listed in Table 1) and the interaction patterns with the bank application (which are listed in Table 2). To do this, we conducted an **expert consensus study** involving 11 experts from the field of gamification or banking. From these 11 experts, eight were HCI experts who were experienced with tailoring designs towards users and had integrated gamification elements before in earlier prototypes. However, to also capture the viewpoint from a non HCI perspective, we also asked three experts who were working in the financial sector on a mobile banking application. Their expert feedback was valuable because they were familiar with categorizing transaction data (and the logic behind those categories) and analyzing mobile banking data.

3.3 Protocol

We provided the participants of the study with two files: one document which explains the study and one coding sheet which has to be filled in afterwards. The experts received a short introduction to the bank application and the Hexad model. This introduction ensured all experts understood the study and prevented confusion concerning the Hexad user types. Next, every expert was asked to fill in the coding sheet where they could map the 105 banking transaction categories from Table 1 and seven interaction pattern with the application from Table 2 onto the six Hexad user types. In each coding sheet, the rows where randomly shuffled. A control row checked whether the experts filled in the coding sheet attentively. Each cell from the coding sheet had to be filled in according to the following four-point scale:

- **0**: This bank transaction category/ interaction pattern has *no significant correlation* to the Hexad user type.
- **1**: This bank transaction category/ interaction pattern *correlates weakly* to the Hexad user type.
- **2**: This bank transaction category/ interaction pattern *correlates moderately* to the Hexad user type.
- **3**: This bank transaction category/ interaction pattern *correlates strongly* to the Hexad user type.

The experts were made clear that no other integer than those stated above could be used (for example no 2.5). Finally, they could explain their thought process in the optional "further clarification" column.

3.4 Data processing

All calculations were executed using IBM SPSS Statistics 23 [20]. To verify the rater agreement, the intraclass correlation (ICC) was calculated [41] on the Hexad user types, the bank transaction categories and the interaction patterns with the application, based on a two-way random fully crossed design with type consistency [17].

According to Hallgren et al. [17], an ICC less than 0.4 is indicative of poor reliability, an ICC between 0.4 and 0.59 is indicative of fair reliability, an ICC between 0.6 and 0.74 is indicative of good reliability and an ICC higher than 0.75 is indicative of excellent reliability. Koo et al. [22] use more stringent criteria. According to them, an ICC of less than 0.5 is indicative of low reliability, an ICC between 0.5 and 0.75 is indicative of moderate reliability, an ICC between 0.75 and 0.9 is indicative of good reliability and an ICC higher than 0.9 is indicative of excellent reliability.

4 RESULTS

We computed ICC's for each Hexad user type as variables of interest with bank transaction categories and interaction patterns with the app considered together as observations. Additionally, we computed ICC's for each of the bank transaction categories and interaction patterns with the app as variables of interest with all Hexad user type considered as observations [34]. Only relationships with an ICC of 0.5 (moderate) or higher were analyzed [22]. This meant we had to remove 45 bank transaction categories from further analysis. Afterwards, the average scores given by the experts for the remaining Hexad user types, bank transaction categories and interaction patterns were calculated. We then removed all bank transaction categories and interaction patterns who had an average score lower than 1.5. We were mainly interested in average scores greater than or equal to 2 because these show that there is a moderate to strong relationship present, but it could be that some bank transaction categories and interaction patterns who had an average score just below the threshold could also be interesting for further analysis. This meant we had to remove an additional 26 bank transaction categories but no interaction patterns with the app. The calculated ICC's from the remaining Hexad user types, bank transaction categories and interaction patterns together with the average scores given by the experts can be found in Table 3.

As illustrated in Table 3, all Hexad user types, except for "Disruptor", had at least one bank transaction category/ interaction pattern with the app has an average score greater than or equal to 2, showing there is indeed a moderate to strong relationship present. Looking at Table 3 in more detail, we can see that there are ten relationships linked to "Socialiser", three to "Player", two to "Achiever" and one to both "Philanthropist" and "Free Spirit".

5 DISCUSSION

The aim of this study was to explore whether a group of experts think that it is possible to derive Hexad user types from mobile banking data. We therefore developed an expert consensus study and let 11 experts in the field of gamification or banking participate in this study.

5.1 Hexad types

All experts had to rate the relation between the six Hexad user types and the 112 bank transaction categories and interaction patterns with the Cake application. After removing all the bank transaction categories and interaction patterns with an ICC lower than 0.5 (45) and an average score for every Hexad user type lower than 1.5 (another 26), we were left with 34 bank transaction categories, seven interaction patterns with the app and all the six Hexad user types, as can be seen in Table 3.

Socialiser The user type that had the most moderate to strong relations present is *Socialiser*. One of the experts declared that activities (for example, "restaurant and bars", "events"...) are related to the *Socialiser* user type because they are "*probably a social activity*". Interacting with others is according to [39] typically for the *Socialiser* user type. Also, for the category "Clothing and accessories" a moderate to strong relation is present. One of the experts explained their rationale: *"clothes are more related to social aspects and self-expressing individuals"*. Finally, two interaction patterns with the app, namely "People recommend Cake to a friend/ family member/. . . and receive one euro from the member gets member program of Cake" and "People share their received rewards from inside the app on social media",

Table 3. Table with the average scores given by the expert. The second row and the second column of the table represent respectively the ICC's of the Hexad user and types and the ICC's of the bank transaction categories and the interaction patterns with the app.

Bank transaction categories		**Philanthropist**	**Socialiser**	**Free Spirit**	**Achiever**	**Player**	**Disruptor**
	ICC	**0.741**	**0.858**	**0.715**	**0.701**	**0.751**	**0.584**
Communication							
Internet	**0.670**	0.3	1.6	1.2	0.9	1.1	1.1
Phone	**0.748**	0.3	1.8	1.1	1.0	0.8	1.0
Food and drinks							
Alcohol	**0.894**	0.3	2.3	0.7	0.6	1.0	0.8
Coffee shops	**0.872**	0.4	2.0	1.4	0.6	0.7	0.4
Restaurant and bars	**0.923**	0.3	2.2	0.8	0.8	1.0	0.3
Health and beauty							
Fitness	**0.822**	0.5	1.7	1.5	2.4	1.3	1.3
Hair and beauty services	**0.746**	0.0	1.6	1.4	0.9	1.0	1.0
Health and beauty products	**0.769**	0.4	1.8	1.5	1.1	0.9	0.8
Healthcare							
Weight loss services	**0.766**	0.1	0.7	0.5	1.5	1.4	0.6
Home							
Garden	**0.868**	0.9	0.6	1.5	0.8	0.3	0.3
Interior	**0.883**	0.7	1.3	1.8	0.5	0.3	0.2
Income							
Cashback	**0.810**	0.4	0.5	0.6	0.8	1.9	0.8
Information and education							
Education fees	**0.797**	1.0	0.3	0.8	1.5	0.4	0.8
School and book fees	**0.842**	1.1	0.3	0.8	1.6	0.4	0.7
Mobility							
Public transport	**0.765**	1.5	1.1	1.4	0.5	0.4	0.5
Pets							
Pet supplies	**0.801**	1.6	0.9	0.8	0.6	0.3	0.5
Savings and investments							
Kids savings	**0.774**	1.5	0.6	0.6	0.8	0.5	0.6
Shopping and services							
Charity	**0.933**	3.0	1.2	1.2	0.9	0.3	0.9
Clothing and accessories	**0.875**	0.3	2.2	1.5	0.8	1.3	0.4
Electronics, computers and software	**0.787**	0.1	1.5	0.9	1.2	1.4	0.6
Jewelry	**0.865**	0.3	1.9	1.2	0.8	0.5	0.3
Parties and celebrations	**0.929**	0.6	2.6	1.0	0.6	0.7	0.8
Sport equipment	**0.830**	0.1	1.2	0.7	1.8	0.9	0.5
Travel and leisure							
Arts and crafts	**0.805**	1.5	0.9	1.8	0.9	0.3	0.5
Associations	**0.818**	1.5	1.5	0.6	1.3	0.3	0.5
Entertainment and night-life	**0.951**	0.8	2.8	1.2	0.9	1.1	0.5
Events	**0.946**	0.9	2.7	1.0	1.2	0.5	0.6
Flights	**0.718**	0.6	1.7	1.4	0.9	0.6	0.7
Hotels and campsites	**0.768**	0.6	1.7	1.4	0.6	0.7	0.7
Leisure activities	**0.872**	0.7	2.2	1.3	1.0	0.9	0.4
Lotteries and bets	**0.863**	0.1	0.6	0.6	0.3	2.1	1.0
Movies	**0.889**	0.6	1.8	1.2	0.4	0.7	0.0
Music and instruments	**0.883**	0.8	1.2	1.8	1.6	0.5	0.0
Sport activities	**0.812**	0.8	1.5	1.1	2.2	1.0	0.5
Interaction patterns with the app							
People change the category of a transaction.	**0.712**	0.6	0.7	1.1	1.3	1.5	1.9
People change the location of a transaction.	**0.790**	0.5	0.5	1.2	1.4	1.2	1.9
People give their bank account in the Cake app a custom name.	**0.795**	0.5	0.9	2.0	1.3	1.3	1.5
People open above avarage the Cake app.	**0.882**	0.2	0.6	0.6	1.3	1.9	1.1
People recommend Cake to a friend/ family member/… and receive one euro from the "member gets member" program of Cake.	**0.912**	0.7	2.3	0.6	1.5	2.5	1.3
People share their received rewards from inside the app on social media.	**0.793**	0.5	2.2	0.9	1.4	1.5	0.8
People shop at a partner of Cake from where they get a special reward from inside the Cake app.	**0.919**	0.5	0.8	0.6	1.9	2.4	0.9

were found to be related to the *Socialiser* user type. The experts explained that they found these two related to the *Socialiser* user type because they create a social interaction with others, which is according to [39] a characteristic of the *Socialiser* user type. There are also other bank transaction categories which just did not make the required average score of 2 or higher for the *Socialiser* user type, like for example "Phone" (1.8), "Health and beauty products" (1.8), "Jewelry" (1.9) etc. These could also be potentially interesting bank transaction categories for the *Socialiser* user type.

Player The *Player* user type has three moderate to strong relations. One of these relations is with the bank transaction category "Lotteries and bets". One of the experts stated that this category is related to the *Player* user type because "*besides addiction, I can't think of other strong incentives to participate in lotteries but receiving rewards*". There are also two interaction patterns with the app which are related to the *Player* user type, namely "People recommend Cake to a friend/ family member/… and receive one euro from the member gets member program of Cake" and "People shop at a partner of Cake from where they get a special reward from inside the Cake app". The experts explained that this relationship is present because both interaction patterns are about receiving (cash) rewards, which has been linked before to the *Player* user type [39].

Achiever The *Achiever* user type has two bank transaction categories which have a moderate to strong relation present. These categories are "Fitness" and "Sport activities". One of the experts explained that this relation is present because people who spend money on these categories "*probably want to master it*". According to [39], the *Achiever* user type is known for proving themselves by tackling difficult challenges. This can potentially be done by spending money on categories like "Fitness" ans "Sport activities".

Free Spirit The *Free Spirit* user type has only one interaction pattern with the app which has a moderate to strong relation, namely giving the bank account in the app a custom name. One of the experts stated that this relation is present because *"customization is often considered characteristic for free spirits in gamification research"*. Despite having only one moderate to strong relation, there are also a few bank transaction categories which just did not make the required average score of 2 or higher for the *Free Spirit* user type. These categories are "Interior" (1.8), "Arts and crafts" (1.8) and "Music and instruments" (1.8). No expert declared why they believed that these categories were linked to the *Free Spirit* user type, but they could be potentially linked to it because *Free Spirits* want to create [39] (for example, change their interior or being busy with arts) and be able to express themselves and act without external control [39] (for example, through making music or through being busy with arts).

Philanthropist The *Philanthropist* user type has one bank transaction category which has a moderate to strong relation present, namely "Charity". All the experts gave this category a score of 3 and one of the experts explained that this is because *"charity is about helping others without getting benefits from it"*. This lays in line with the definition from [39] of the user type.

Disruptor Finally, the *Disruptor* user type has no moderate to strong relation with any of the financial transaction data. Despite this, there are 2 interaction patterns with the app who both score an average score of 1.9, namely "People change the category of a transaction" and "People change the location of a transaction". The experts gave no reason why they believe that these two interaction patterns are potentially linked to the *Disruptor* user type, but it could be because the *Disruptor* user type is known for trying to change inside the system [39].

5.2 Reflection

The research community is increasingly questioning whether or not gamification preferences of a person change through time [7, 18]. To address this question, the results from this paper can serve as a starting point for further research whether hexad user profiles could be recalculated quickly and easily on a regular basis out of mobile banking data. Due to the fact that only some Hexad user types had one moderate to strong relation between a Hexad user type and a bank transaction category/interaction pattern, we need to remain critical and verify whether mobile banking data on itself could be used to derive Hexad user types. However, if we can find a sufficient distinction between multiple Hexad user types, we might be able to personalize the system to some extend.

Personalized gamification has several beneficial uses cases, such as supporting users in making smarter (financial) decisions through tailored motivational messages. However, this technology could also be used abusively by using tailored gamification to sell for example products, services etc. This raises serious concerns regarding ethics and privacy [24, 35]. To avoid situations as much as possible where tailored gamification is used abusively, policymakers need to ensure that individuals are protected against abuse of such technologies. Of course, we can not lay all responsibility with the policymakers, as companies and institutions who make use of such technologies need to investigate how they can be as transparent as possible about it towards their end users.

6 CONCLUSION, LIMITATIONS AND FUTURE WORK

This study explored whether a group of experts think that mobile banking data can be used to automate the profiling of Hexad user types. To this end, 11 experts in the field of gamification or banking mapped associations of Hexad user types and bank transaction categories/ interaction patterns with the app. We found that experts correlated five out of six Hexad user types at least moderately to one bank transaction category/ interaction pattern with the app. Our exploratory results suggest that leveraging financial transaction data could have the potential to automate Hexad profiling. The applications, however, should not be limited to the financial domain, but can be broadly applied in all domains where gamification is used to increase motivation [13], engagement [33], or adherence [9].

One of the limitations of this study is that the current results do not take into consideration whether or not the relations between the Hexad user types and mobile banking data is positive or negative correlated. It could be for example that some relations which currently have no significant to a weak correlation are actually negatively correlated. Also, this study did not take into account data such as number of transactions per month or average value per transaction. It could be for example that experts believe that Players might save less than others as they want to reward themselves more frequently. Finally, although 11 different experts is a good starting point for this study, it is not indicative for the real-life relationship between Hexad user types and mobile banking data. A real-life experiment is needed to validate the exploratory results from this study. To do this, real, time-stamped, mobile banking data should be collected over a longer period of time, analyzed, and compared with regular measurements using the validated Hexad survey [39].

7 ACKNOWLEDGMENTS

We would like to thank all experts. This work is part of the research projects Personal Health Empowerment with project number HBC.2018.2012 financed by Flanders Innovation & Entrepreneurship and the Personalized and connected food service providers (PERSFO) project financed by EIT-Food with project ID 20291.

REFERENCES

[1] Aisha Muhammad Abdullahi, Kiemute Oyibo, Rita Orji, and Abdullahi Abubakar Kawu. 2019. The influence of age, gender, and cognitive ability on the susceptibility to persuasive strategies. *Information* 10, 11 (2019), 352.

[2] Maximilian Altmeyer, Pascal Lessel, Marc Schubhan, and Antonio Krüger. 2019. Towards predicting hexad user types from smartphone data. In *Extended Abstracts of the Annual Symposium on Computer-Human Interaction in Play Companion Extended Abstracts*. Association for Computing Machinery, Inc, Barcelona, 315–322.

[3] Maximilian Altmeyer, Marc Schubhan, Pascal Lessel, Linda Muller, and Antonio Krüger. 2020. Using Hexad User Types to Select Suitable Gamification Elements to Encourage Healthy Eating. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, 1–8.

[4] Maximilian Altmeyer, Gustavo F Tondello, Antonio Krüger, and Lennart E Nacke. 2020. HexArcade: Predicting Hexad User Types By Using Gameful Applications. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*. Association for Computing Machinery, Inc, New York, 219–230.

[5] M Andrzej. 2015. Even Ninja Monkeys Like to Play: Gamification, Game Thinking and Motivational Design.

[6] Cake. 2019. *Cake. The profitable banking app.* Cake. https://cake.app/

[7] Ana Cláudia Guimarães Santos, Wilk Oliveira, Juho Hamari, and Seiji Isotani. 2021. Do people's user types change over time? An exploratory study. *arXiv e-prints* 5 (2021), arXiv–2106.

[8] Jacob Cohen. 2013. *Statistical power analysis for the behavioral sciences.* Academic press, New York, San Francisco, London.

[9] Robin De Croon, Jonas Geuens, Katrien Verbert, and Vero Vanden Abeele. 2021. A Systematic Review of the Effect of Gamification on Adherence Across Disciplines. In *HCI in Games: Experience Design and Game Mechanics*, Xiaowen Fang (Ed.). Springer International Publishing, Cham, 168–184.

[10] Sebastian Deterding, Dan Dixon, Rilla Khaled, and Lennart Nacke. 2011. From game design elements to gamefulness: defining" gamification". In *Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments*. Association for Computing Machinery, Inc, Tampere, Finland, 9–15.

[11] Tobias Ebert, Friedrich M Götz, Joe J Gladstone, Sandrine R Müller, and Sandra C Matz. 2020. Spending reflects not only who we are but also who we are around: The joint effects of individual and geographic personality on consumption. *Journal of Personality and Social Psychology* 48 (2020), 825–830.

[12] Golnoosh Farnadi, Susana Zoghbi, Marie-Francine Moens, and Martine De Cock. 2013. Recognising personality traits using facebook status updates. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 7. AAAI, Boston, USA, 5 pages.

[13] Jonas Geuens, Luc Geurts, Kathrin Gerling, Robin De Croon, and Vero Vanden Abeele. 2019. A dyad of lenses for the motivational design of mHealth: Bridging the gap between health theory and app design. In *2019 IEEE International Conference on Healthcare Informatics (ICHI)*. IEEE, Xi'an, China, 1–12.

[14] Jonas Geuens, Thijs Swinnen, Luc Geurts, Rene Westhovens, Robin De Croon, and Vero Vanden Abeele. 2020. Worriers versus Warriors: Tailoring mHealth to Address Differences in Patients with Chronic Arthritis. In *2020 IEEE International Conference on Healthcare Informatics (ICHI)*. IEEE, Oldenburg, Germany, 1–12. https://doi.org/10.1109/ICHI48887.2020.9374322

[15] Karsten Gielis, Robin De Croon, Paul Dierick, Filipa Brito, Lies Van Assche, Jos Tournoy, and Vero Vanden Abeele. 2021. Dissecting Digital Card Games to Yield Digital Biomarkers for the Assessment of Mild Cognitive Impairment: a Methodological Approach and Exploratory Study. Journal of Medical Internet Research. (accepted).

[16] Theo Downes-Le Guin, Reg Baker, Joanne Mechling, and Erica Ruyle. 2012. Myths and realities of respondent engagement in online surveys. *International Journal of Market Research* 54, 5 (2012), 613–633.

[17] Kevin A Hallgren. 2012. Computing inter-rater reliability for observational data: an overview and tutorial. *Tutorials in quantitative methods for psychology* 8, 1 (2012), 23.

[18] Stuart Hallifax, Audrey Serna, Jean-Charles Marty, and Elise Lavoué. 2021. Dynamic gamification adaptation framework based on engagement detection through learning analytics. *Companion Proceedings 11th International Conference on Learning Analytics & Knowledge (LAK21)* 11 (2021), 14 pages.

[19] Stuart Hallifax, Audrey Serna, Jean-Charles Marty, Guillaume Lavoué, and Elise Lavoué. 2019. Factors to consider for tailored gamification. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*. Association for Computing Machinery, Barcelona, Spain, 559–572.

[20] IBM. 2021. *Downloading IBM SPSS Statistics 23.* IBM. Retrieved May 25, 2021 from https://www.ibm.com/support/pages/downloading-ibm-spss-statistics-23

[21] Olena Kaminska, Allan L McCutcheon, and Jaak Billiet. 2010. Satisficing among reluctant respondents in a cross-national context. *Public Opinion Quarterly* 74, 5 (2010), 956–984.

[22] Terry K Koo and Mae Y Li. 2016. A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of chiropractic medicine* 15, 2 (2016), 155–163.

[23] Andrzej Marczewski. 2013. *A Player Type Framework for Gamification Design.* Gamified. Retrieved May 24, 2021 from https://www.gamified.uk/user-types/

[24] Andrzej Marczewski. 2017. The ethics of gamification. *XRDS: Crossroads, The ACM Magazine for Students* 24, 1 (2017), 56–59.

[25] Böckle Martin and Yeboah-Antwi Kwaku. 2019. Designing at the intersection of gamification and persuasive technology to incentivize energy-saving. In *Conference on e-Business, e-Services and e-Society*. Springer, Springer, Cham, Trondheim, Norway, 316–328.

[26] Alberto Mora, Gustavo F Tondello, Laura Calvet, Carina González, Joan Arnedo-Moreno, and Lennart E Nacke. 2019. The quest for a better tailoring of gameful design: An analysis of player type preferences. In *Proceedings of the XX International Conference on Human Computer Interaction*. Association for Computing Machinery, Donostia Gipuzkoa, Spain, 1–8.

[27] Lennart E Nacke and Christoph Sebastian Deterding. 2017. The maturing of gamification research. *Computers in Human Behaviour* 71 (2017), 450–454.

[28] Elnaz Nasirzadeh and Mohammad Fathian. 2020. Investigating the effect of gamification elements on bank customers to personalize gamified systems. *International Journal of Human-Computer Studies* 143 (2020), 102469. https://doi.org/10.1016/j.ijhcs.2020.102469

[29] Jeroen Ooge, Robin De Croon, Katrien Verbert, and Vero Vanden Abeele. 2020. Tailoring Gamification for Adolescents: a Validation Study of Big Five and Hexad in Dutch. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*. Association for Computing Machinery, Virtual Event, Canada, 206–218.

[30] Kiemute Oyibo, Rita Orji, and Julita Vassileva. 2017. The influence of culture in the effect of age and gender on social influence in persuasive technology. In *Adjunct publication of the 25th conference on user modeling, adaptation and personalization*. Association for Computing Machinery, Bratislava, Slovakia, 47–52.

[31] Jon Puleston. 2011. Online research–game on!: A look at how gaming techniques can transform your online research. In *Shifting the Boundaries of Research. Proceedings of the 6th ASC (Association for Survey Computing) International Conference*. University of Bristol, Berkeley, UK, 20–50.

[32] Richard M Ryan and Edward L Deci. 2000. SDT and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist* 55, 1 (2000), 68–78.

[33] Katie Seaborn and Deborah I Fels. 2015. Gamification in theory and action: A survey. *International Journal of human-computer studies* 74 (2015), 14–31.

[34] Patrick E Shrout and Joseph L Fleiss. 1979. Intraclass correlations: uses in assessing rater reliability. *Psychological bulletin* 86, 2 (1979), 420.

[35] Andrea Stevenson Thorpe and Stephen Roper. 2019. The ethics of gamification in a marketing context. *Journal of business ethics* 155, 2 (2019), 597–609.

[36] Gustavo F Tondello, Alberto Mora, Andrzej Marczewski, and Lennart E Nacke. 2019. Empirical validation of the gamification user types hexad scale in English and Spanish. *International Journal of Human-Computer Studies* 127 (2019), 95–111.

[37] Gustavo Fortes Tondello and Lennart E Nacke. 2018. Towards Customizing Gameful Systems by Gameful Design Elements.. In *PPT@ PERSUASIVE*. Springer, Waterloo, Canada, 102–110.

[38] Gustavo F Tondello and Lennart E Nacke. 2020. Validation of User Preferences and Effects of Personalized Gamification on Task Performance. *Frontiers in Computer Science* 2 (2020), 29.

[39] Gustavo F Tondello, Rina R Wehbe, Lisa Diamond, Marc Busch, Andrzej Marczewski, and Lennart E Nacke. 2016. The gamification user types hexad scale. In *Proceedings of the 2016 annual symposium on computer-human interaction in play*. Association for Computing Machinery, Austin Texas, USA, 229–243.

[40] Leen Van Houdt, Martijn Millecamp, Katrien Verbert, and Vero Vanden Abeele. 2020. Disambiguating Preferences for Gamification Strategies to Motivate Pro-Environmental Behaviour. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*. Association for Computing Machinery, Virtual Event, Canada, 241–253.

[41] Alexander Von Eye and Eun Young Mun. 2014. *Analyzing rater agreement: Manifest variable methods.* Psychology Press, New Jersey, USA.