Player-Type-based Personalization of Gamification in Fitness Apps

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Abstract: This paper examines the effect of personalized gamification on an individual's motivation in the context of fitness apps. In a first study, we evaluate the four categorization models "Bartle Player Types", "Big Five", "Hexad User Types", and "BrainHex" on their ability to predict individual gamification preferences of users and develop a new prediction model called "MoMo". Bartle, BrainHex, and MoMo are validated empirically in a second study, employing off-the-shelf fitness apps with gamification elements. The results of both studies indicate that a prediction is possible using the categorization models. Among all models, MoMo performs best in predicting individual gamification preferences, followed by BrainHex. Results of the second study indicate that, although the models MoMo and BrainHex perform better in predicting the theoretical rating of gamification elements than the random model, the prediction of the real motivation value in a specific fitness app is more difficult. This may be due to the concrete implementation of the elements in the second study, and due to the general problem of (theoretically) rating gamification elements without having experienced them in a real application.

1 INTRODUCTION

Fitness apps aim to support users in enhancing their health. One goal thereof is to increase the motivation of the users to engage in sports. The present study, therefore, examines the influence of individualized gamification on the increase of motivation in the context of fitness apps.

Gamification has its origins in the digital media industry, where its first use is documented in 2008 (Deterding et al., 2011). The definition of Deterding et al. (2011) is mostly used in literature, defining it as: "the use of game design elements in non-game contexts". Later on, Werbach (2014) presents a revised definition of the term gamification: In his opinion, gamification should be defined as a process of making activities playful. He justifies this with the fact that not everything containing a game element automatically generates gamification, but rather that the entire experience in a system is important.

Whether the applied gamification of a system achieves the desired effect, e. g. an increase in motivation to eat a healthy diet or do sports, depends on the personal preferences of each individual user (Ferro, 2018). A possible approach for personalized gamification is the categorization of users by means of categorization models like the Bartle Player Types and a personalized gamification design that is derived from these models. Some researchers have already worked on the evaluation of categorization models for the personalization of gamification. Kocadere and Çağlar (2018) examined the influence of the Bartle Player Types on gamification preferences; their results show differences (albeit small) between the different types. The effects of the Big Five personalities on the preferences for game elements of users have also been investigated in several studies, such as Ferro (2018). However, their results indicate that they have little impact. The Hexad User Types are evaluated in several studies on the personalization of gamification, for example by Mora et al. (2019) who found correlations between the User Types and gamification preferences. In contrast to the studies mentioned above, Hallifax et al. (2019) do not focus on a single model but compare the three models BrainHex, Hexad, and Big Five in terms of their influence on gamification preferences. The results of the study show that Hexad is most suitable for predicting preferences (Hallifax et al., 2019).

This previous research shows that categorization by categorization models is promising with regard to the prediction of personal preferences in gamification.

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However, most of these studies focus on only one of the categorization models.

This paper focuses on the comparison of four models (Bartle, Big Five, Hexad, and BrainHex), and on developing a specific model of the motivational value (MoMo for short) using a set of questions from the four categorization models to predict preferences in gamification elements. Besides, many of the studies mentioned above were only conducted in the laboratory and the participants had to rate the patterns without "playing" with them. In our second study, we asked the participants to rate the patterns before and after the extensive use of real fitness apps implementing gamification patterns.

The remainder of this paper is structured as follows: Chapter 2 specifies a set of relevant gamification elements, derived from literature. Chapter 3 describes the four used categorization models. Chapter 4 explains our methodological approach, chapter 5 (study 1) and chapter 6 (study 2) describe the methods and results of the two conducted studies. Finally (chapter 7), we discuss the results and possible implications.

2 GAMIFICATION ELEMENTS

To develop a model that can predict the gamification preferences of users, it is necessary to first determine which different gamification elements exist. For this purpose, we developed a list of 30 gamification elements based on gamification elements mentioned in the literature (see Table 1).

3 CATEGORIZATION MODELS

To determine preferences, we applied categorization models for player types. These serve as a basis for differentiating between participants in order to identify differences and similarities in their preferences. Various categorization models are discussed in the literature, of which four of the best-known models are used in this study. These categorization models are the following.

3.1 Bartle Player Types

The Bartle Player Types are known as one of the most basic categorizations of players (Kocadere & Çağlar, 2018). They were developed by the British professor Richard Bartle and are based on the Multi-User Dungeons genre (Bartle, 1996). The Bartle Player Types contain the following four player types: **Achiever** ("Acting on the World"), **Explorer** ("Interacting with the World"), **Killer** ("Acting on other Players"), and **Socializer** ("Interacting with other Players") (Bartle, 1996).

To determine the Bartle Player Types, we used the Bartle Test developed by the authors González Mariño et al. (2018). As the questions of the test itself are not mentioned in the paper González Mariño et al. (2018), we requested them from the authors by e-mail.

3.2 Big Five

The Big Five, also known as the OCEAN model, is a widely used personality model (Suryapranata et al., 2020). The five dimensions of the Big Five are defined by Rammstedt et al. (2013) as follows: **Agreeableness** (a person's behavior towards other people), **Conscientiousness** (behavior of a person during the completion of a task), **Extraversion** (behavior of a person towards their environment), **Neuroticism** (emotional stability of a person), and **Openness to experience** (how interested a person is in new things).

In this paper, for the determination of the Big Five, the test "10 Item Big Five Inventory" (short: BFI-10) by Rammstedt et al. (2013) is used.

Table 1: List of gamification elements with definitions. Mentions of the elements in the literature: 1 = Arango-López et al. (2017), 2 = Chou (2016), 3 = Deterding et al. (2011), 4 = Ferro (2018), 5 = Hallifax et al. (2019), 6 = Kocadere and Çağlar (2018), 7 = Raftopoulos et al. (2015), 8 = Suryapranata et al. (2020), 9 = Swacha and Muszyńska (2016).

Achievement Symbol [2, 3, 4, 5, 6, 7, 8]	Discussionboard [5]	Progress Bar [1, 2, 4, 5, 9]
Assessment [9]	Feedback [2, 3, 8, 9]	Record [6, 9]
Avatar [2, 4, 8, 9]	Gift [1, 2, 4, 6, 9]	Reward [1, 2, 4, 5, 6, 9]
Brag Button [2, 9]	Leaderboard [1, 2, 3, 4, 5, 6, 7, 9]	Schedule [2, 5, 9]
Challenge [1, 2, 3, 4, 7, 9]	Level [2, 3, 4, 5, 6, 8, 9]	Social Feedback [1]
Choice [2, 9]	Number Limit [2]	Social Graph [9]
Collection Set [2, 9]	Performance Graph [2, 9]	Team [2, 5, 6, 9]
Unlocking [2, 4, 6, 9]	Permadeath [4]	Time Limit [1, 2, 3, 4, 5]
Crowning [2, 7, 9]	Points [1, 2, 4, 5, 6, 7, 9]	Topic [2, 4, 6, 8, 9]
Difficulty Selection [4]	Prize Pacing [2, 9]	Torture Break [2, 9]

3.3 Hexad User Types

The Hexad User Types were developed by Andrzej Marczewski to provide a user-type model specifically for gamification (Hallifax et al., 2019). Marczewski (2016) describes the following user types: **Achiever** (intrinsically motivated by mastery), **Free Spirit** (intrinsically motivated by autonomy), **Philanthropist** (intrinsically motivated by purpose and meaning), **Socializer** (intrinsically motivated by relatedness), **Disruptor (**extrinsically motivated by change), and **Player** (extrinsically motivated by rewards).

The test developed by Tondello et al. (2016) is the official test for the determination of the Hexad User Types and is used in this study.

3.4 BrainHex

The BrainHex was developed by the company International Hobo Ltd. (2011). It was developed based on existing research on players and knowledge of underlying neurobiological mechanisms (Nacke et al., 2011). The BrainHex types contain the following types: **Achiever (**is motivated by long-term success), **Conqueror** (does not want to win easily in a game), **Daredevil** (seeks the thrill and the risk), **Mastermind** (wants problems for which a strategy is needed), **Seeker** (enjoys moments of wonder), **Socializer** (is focused on the other people), and **Survivor** (enjoys strongly negative experiences such as terror) (Nacke et al., 2011).

The BrainHex types can be determined by a questionnaire, which is available online (International Hobo Ltd., 2019). The evaluation of the test was not published completely. Therefore, we derived its categorization logic by reverse engineering, using the publication of Nacke et al. (2011) as well as the displayed results on the website of International Hobo Ltd. (2019).

4 METHODS

To develop and validate a model based on users' categorization models, we first conducted a user research (study 1) to determine the preferences in gamification elements of users. Based on the results of this first study, we compared the different categorization models and developed subsequently the motivational value model (MoMo) for predicting preferences. Finally, we validated the prediction power of MoMo, Bartle, and BrainHex for fitness in a second study.

5 USER RESEARCH (STUDY 1)

5.1 Methods for User Research

Our first user research served for a better understanding of the users' preferences in gamification patterns and their relationships to the various models for categorizing users. Based on these results, we developed models for predicting preferences.

To collect the data of study 1, we developed a questionnaire. It uses the tests mentioned above to determine the Bartle Player Types, Big Five, Hexad User Types, and BrainHex Types. Additionally, a few demographic data are requested and the participants are asked to rate the 30 elements on a 5-Likert scale from "demotivates me very much" through "neutral" to "motivates me very much", supported by a definition and a descriptive image. We tested the questionnaire in a pilot study and subsequently adjusted it, based on the results.

For the evaluation of the survey, we made a distinction between players and non-players, by using the question "How many hours do you play per week?". We wanted to find out whether there are differences between players and non-payers. Participants who play more than 2 hours per week were classified as "players", whereas those who play two or fewer hours per week were classified as "non-players".

We used linear regression analysis to calculate regression models for predicting the preferences of each gamification element. For this purpose, we performed multiple regression per gamification element and categorization model, using the method "stepwise". Finally, we compared the average R^2 value and the number of predictable gamification patterns between the five models. The resulting regression models are used as the basis for the calculation of preferences in study 2 (see section 4.4).

5.2 Creating the Model of Motivational Value (MoMo)

To create the MoMo, we used a correlation matrix in which all questions and results of the four categorization models are correlated with the ratings of the gamification elements. Such a correlation matrix is created for players, non-players, and all participants. Using the correlation matrixes, we selected all questions and results of the models whose significance value is less than 0.01 or, if not available, less than 0.05, for multiple linear regression. For each gamification element, the regression model with the highest R^2 value and the lowest significance value is selected.

Afterward, we compared the regression models of all participants, all players, and all non-players. This makes it possible to determine whether there are major differences between the models of players and non-players. Furthermore, the best regression model can be selected for each gamification element individually by deciding whether a division into player and non-player is appropriate.

5.3 Results

5.3.1 Description of the Sample

We collected the survey data in the period from May 5th, 2020 to May 20th, 2020. For this purpose, we invited the participants via email to complete the questionnaire online. A total of 122 participants fully completed the survey. Of the participants, 56.6 % were male and 43.4 % female, which makes the distribution quite balanced. Less balanced, however, is the distribution in age: the sample consisted of persons aged 18-64 years, with almost three-quarters of the respondents between 18 and 30 years old, 16.4 % of the participants between 31 and 40 years old, and just under 11 % over 40 years old. The categorization of players and non-players results in a distribution of 59.1 % players and 40.9 % non-players. 7 participants did not provide any information about the playing time and therefore could not be classified.

5.3.2 Differentiation of Players and Non-Players

After analyzing the individual regression models for MoMo for players, non-players, and all participants in total, the regression models for all participants performed worse than the regression models for players and non-players separately. Therefore, we carried out further evaluations separately, for players and non-players only.

5.3.3 Comparison of the Models

We compared the four user categorization models as well as the MoMo based on the R^2 value and the number of significantly predictable gamification elements, divided into players, non-players, and all participants. Figure 1 shows that MoMo is the only model that can predict all 30 gamification elements for players, non-players, and all participants. Thus, the MoMo scores best in this comparison, followed by BrainHex and Hexad. For players, the Big Five are the least suitable, with only 15 predictable elements. For non-players and all participants, however, Bartle scores the worst in this comparison. The opposite is true when comparing the coefficient of determination, where BrainHex is best for both players and non-players. The coefficient of determination of the Big Five and Bartle models is also opposite to the number of predictable elements. For players, both models have the same coefficient of determination. For non-players and all participants, however, the coefficient of determination of Bartle is greater than that of Big Five.

To validate the models in a subsequent study 2, we included the two best models from study 1. These are MoMo and BrainHex. Since MoMo covers all questions of Bartle, Bartle is also implicitly included in the validation.

6 VALIDATION (STUDY 2)

6.1 Methods for Validation

Based on the results of the user research, the two best models are selected for validation: MoMo and BrainHex. The goal is to validate whether the prediction of preferences is possible with these two models. For this purpose, we conducted a longitudinal study over two weeks. Participants first filled out an online questionnaire (questionnaire 1) that contains the same questions as the questionnaire of study 1 but shortened to the questions necessary for the prediction. After completing the questionnaire, we asked the participants to use a fitness app which they should test for about one week. Two real fitness apps were available for this purpose, both containing various gamification elements. For the selection, we first tested different fitness apps and evaluated them according to the criteria of the checklist with the quality criteria catalog of the Technical University of Dortmund (Reh@pp-Quality, 2016). Due to the relatively comparable range of functions, the same quality evaluation, and different gamification elements contained in the apps, MyFitnessPal and Virtuagym were selected for validation. After the test, the participants filled out a second questionnaire (questionnaire 2) containing the same questions as the first questionnaire of study 2, and additionally the ratings of the gamification elements implemented by the tested app and their influence on the motivation to engage in sports. Furthermore, we conducted a semi-structured interview with four participants to evaluate the gamification elements tested. The participants were randomly selected.

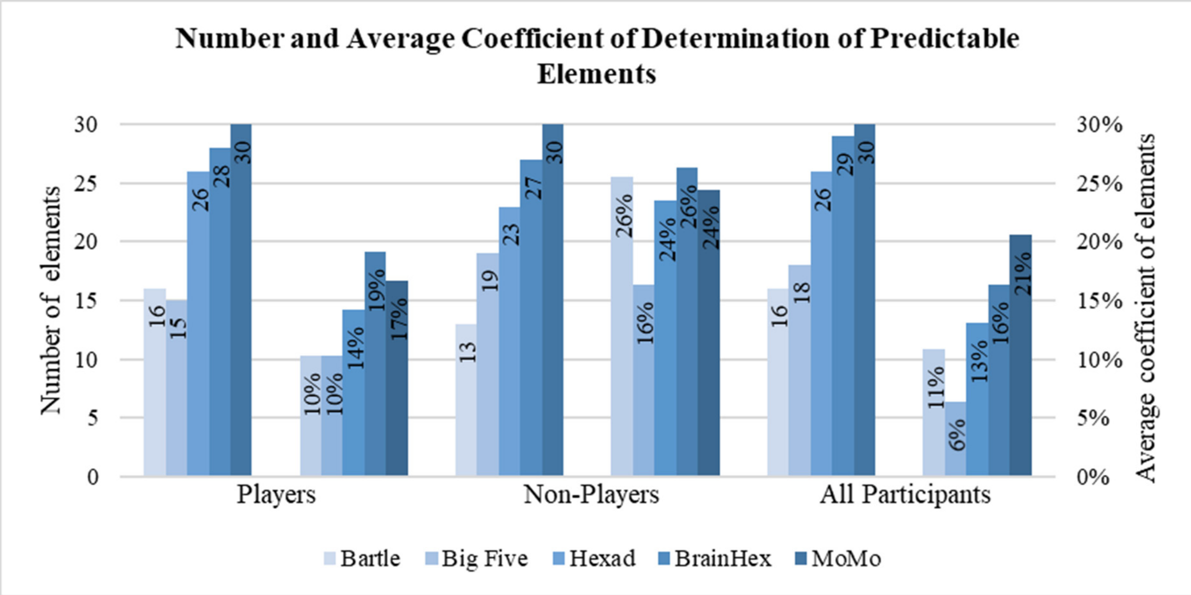

Figure 1: Comparison of the five models Bartle, Big Five, Hexad, BrainHex and MoMo in the number and average coefficient of determination of predictable elements.

To compare the participants' preferences of gamification elements with the predictions calculated by the models, both the real and the calculated ratings are categorized according to the following scheme:

- Min – 2.5 = "demotivated"
- 2.5 – 3.5 = "neutral"
- 3.5 – Max = "motivated"

The values resulting from the categorization can then be compared by analyzing whether the prediction and the rating are the same ("correct prediction") or not ("incorrect prediction"). To compare the models and evaluate the quality of the predictions, we determined the number of correctly predicted scores per gamification element and participant. For the evaluation of the prediction quality, we compared the number of correct predictions with a random model, derived from a normal distribution of the three categorization possibilities ("motivated", "neutral", "demotivated"). Due to the three categorization possibilities, the expected value of this random model is 1/3. This results in a random model of 10 out of 30 correct predicted gamification elements per participant. Consequently, for 6 out of 19 participants, the preference in a gamification element is correctly predicted.

For the validation of the predictions in real apps, however, the random model is calculated for each gamification element individually, since some participants had missed a gamification element in the app and therefore could not rate it. With participants not rating some elements, a fixed random model could falsify the results. This falsification can be prevented by calculating the random model in the following way: multiplying the number of participants who have seen the element in the app by 1/3.

6.2 Results

6.2.1 Description of the Sample

We collected the data in the period from July 20th, 2020 to August 7th, 2020, by inviting participants via email to participate in the study. A total of 19 participants took part in the study. Of the participants, 57.9 % were female and 42.1 % male. The sample consisted of persons aged 22-54 years, but more than two-thirds of the participants were between 18 and 30 years old, 26.3 % were between 31 and 40 years old, and only one person was over 40 years old. Categorizing players and non-players results in a distribution of 57.9 % players and 42.1 % non-players.

6.2.2 Prediction Quality

The comparison in the number of correctly predicted preferences per participant (before they used the app), which is illustrated in Figure 2, shows that MoMo performs best with a mean of 17.11 correct element

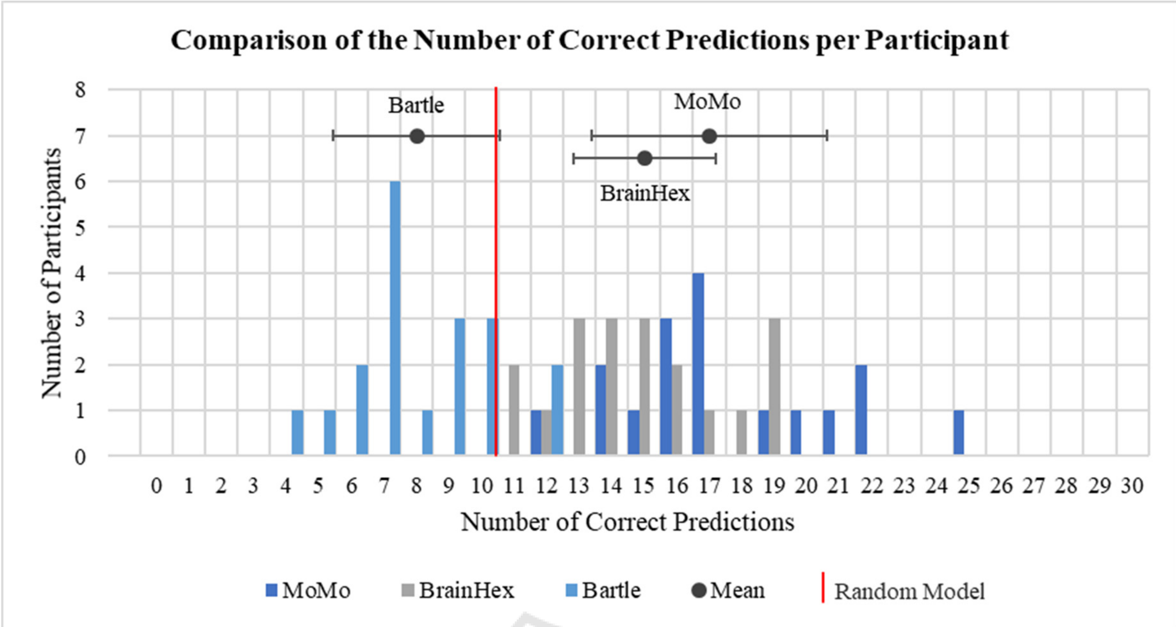

Figure 2: Comparison of the number of correct predictions per participant in questionnaire 1 of study 2 and mean for each model with standard deviation.

predictions per participant, followed by BrainHex (14.95) and Bartle (8.00). A t-test shows, that the differences between all models are significant. The mean value of MoMo and BrainHex is clearly above the random model of 10 elements. In contrast, the mean value of Bartle is significantly below the random model.

Furthermore, these tendencies are also shown by the comparison of the preference predictions and the real rating of the gamification elements: MoMo with an average of 57 % correct predictions in questionnaire 1 has the best results, followed by BrainHex with 50 %, and Bartle with 27 %. Considering the prediction quality for each of the 30 gamification elements separately, the MoMo is above or equal to the random model (6 out of 19 correct predictions per element) for all elements. For BrainHex, the predictions of 27 elements are better or equal to the random model, and for Bartle 12 elements.

These tendencies are continued in the results of questionnaire 2, where the MoMo is the best performing and Bartle the worst for all evaluations. However, percentages of correct predictions rise slightly for all models: MoMo 60 %, BrainHex 52 %, and Bartle 29 %. The same applies to the comparison of correct predictions per participant, where the mean values of each model increase slightly: MoMo 18.00, BrainHex 15.74, and Bartle 8.26.

6.2.3 Validation of the Predictions in Real Apps

The validation of the preferences with the ratings in the real apps (after using the app) shows a different result from the theoretical prediction quality (before using the app). Nevertheless, the distribution of the three models remains the same: Out of 43 elements that were used in the real apps, the MoMo is the strongest with 32 elements predicted correctly, followed by BrainHex with 28 elements, and Bartle with 19 elements. Note that the random model would predict 2 elements correctly on average. The MoMo can thus correctly predict 33 % of the preferences, BrainHex 29 %, and Bartle 19 %. Since the random model achieves 27 %, both MoMo and BrainHex are slightly better than the random model.

7 DISCUSSION OF THE RESULTS

The results of the user research (study 1) show that all models are suitable to predict preferences for at least some elements. However, the comparison of the different models shows that there are considerable differences in the quality and number of the predictions. Of the four categorization models, BrainHex scores best. Furthermore, the results for the creation of the motivational value model (MoMo) show that by combining all four categorization models, it is possible to create an even better model for predicting preferences.

The quality evaluation of the predictions (study 2) shows, that the users' theoretical ratings of gamification elements can be predicted well since both, MoMo (57% correct predictions) and BrainHex (50% correct predictions) perform better than the random model, whereas Bartle (27% correct predictions) scores worse.

Nevertheless, the comparison of the results of questionnaire 1 and 2 shows variances in the distribution of correct predictions per element, which can be attributed to the varying ratings of the gamification elements by the participants in questionnaire 1 and 2: only 65 % of the elements in questionnaire 1 and 2 were rated the same. In contrast, the predictions differ less: 12 % of the predictions in MoMo differ, 13 % in BrainHex, and 7 % in Bartle. This suggests that answering the questionnaires of the models is relatively stable, but a theoretical rating of the gamification elements is difficult for the participants. However, it is also possible that the ratings may have changed due to experiences in the apps. For this reason, it would be reasonable to test whether the ratings stabilize over time in a long-term study.

In contrast, the validation of the ratings of the elements in the real apps (after having used the app) shows a lower prediction quality compared to the theoretical ratings (before using the app), while the distribution of the models remains the same: The MoMo (33 % correct predictions) is the strongest followed by BrainHex (29 % correct predictions), and Bartle (19 % correct predictions). The strong decrease of percentages is based on the equally strong variation in the ratings of the elements in theory and the real apps: only 32 % of the ratings match between before and after use of the apps. This may be due to two reasons: First, as mentioned above, the theoretical rating of the gamification elements may be difficult for the participant, and therefore the data from the regression analysis, which is based on the theoretical data, may not match the real ratings. Second, it may be caused by the implementation of the gamification elements in the apps since a bad implementation is rated worse than a good one, which may lead to differences. This was partially confirmed by the interviews in which it was apparent for some elements that they would be motivating in principle but did not influence the participants in the actual test phase. For example, the element "Challenge" was rated theoretically as motivating. However, since there were no suitable challenges, it was rated rather neutral after having used the real app. Furthermore, the validation performed in this study, as well as the data collection, was based on solely subjective ratings and did not measure the objective increase or decrease in motivation through certain gamification elements.

Moreover, with 19 participants in the second study, quantitative validation of the data was not possible, which is why the validation should be repeated by a study with a significantly larger sample size. In addition, other quality features of the predictions should be considered, since it cannot be ensured that the ratings were normally distributed and thus the 1/3 random model may not be applicable for every element.

8 CONCLUSIONS

The results of this study indicate that gamification preferences can be predicted using the Bartle, Big Five, Hexad, and BrainHex categorization models. In comparison, BrainHex scores best and Bartle scores worst. The results also show that by combining the four categorization models, a model (MoMo) could be developed that can predict preferences even better than the four individual categorization models. In the validation, it becomes clear that the prediction of the models for the theoretical rating of gamification elements is significantly higher than the random model for both BrainHex and MoMo. The prediction of the motivational value after having experienced a real app is much more difficult. Reasons for the rather poor predictability of the preferences in the real apps may be the concrete implementation of the elements or the fact that the elements are difficult to rate without having experienced them in a real app.

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