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Using Player Type Models for Personalized Game Design – An Empirical Investigation

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Abstract. Personalized games should provide a better player experience than one-size-fits-all games. As a method for personalization, player type models have been discussed recently. Player type models would be useful tools in the personalization of games, if they have a relationship to the players' experience of specific game mechanics. However, this relationship has never been empirically investigated. To close this gap, we examine whether player types—as a specific appearance of personality traits—can significantly and reliably predict player experience. We investigate the predictive power of two player types (Mastermind, Seeker) of the BrainHex player type model. Results of a field study (n = 51) with a mobile game prototype tailored to the two player types Mastermind and Seeker suggest that player type models still need improvement: Player type scores do not significantly predict player experience of according game mechanics. We discuss possible explanations and a way to design personalized games that adapt to users gaming preferences with player type models.

Keywords: Player Types, Player Type Models, Personalization, Games

1 Introduction

Games are in the focus of both academia and industry. For industry, digital games are a growing market, as surveys show that for example over 59%[1] of Americans play games. For academia, games are a promising opportunity to solve central societal challenges such as unhealthy lifestyles and environmental pollution through research and development of serious [1] and persuasive [2] games. These are games to stimulate learning processes and to initiate behavioral change towards a positive direction.

[1] http://www.bigfishgames.com/blog/stats/

A critical challenge for game designers and developers—whether in academia or industry—is to ensure that people actually enjoy their games and thus play them frequently. One way to increase the players' engagement is to design games around individual preferences for certain game mechanics. Gameplay mechanics (such as solving puzzles or exploring new areas) that are enjoyed by one kind of player (group) might not be appealing to another kind of player (group).

To personalize games, player (or gamer) type models are a frequently discussed and applied paradigm in the gaming community [3–5], especially in the field of persuasive games [6, 7]. Player types characterize players according to their preferences for general game mechanics. These models suggest that certain player types are more or less receptive to specific game mechanics. Therefore, games which contain game mechanics that fit the players' type are hypothesized to lead to a better player experience. The general concept of player type models shares similarities with personality trait models, such as the Big Five factor model [8]: Both aim at capturing (more or less) stable individual differences, which can be used for describing humans and explaining differences in behavior and underlying attitudes. In that sense, personality trait models can be seen as a higher-level conceptualization of individual differences (not directed at certain areas or behaviors), whereas player type models are more specific and focused at explaining differences in player behavior, experience and emotions. Also empirically these shared similarities[2] of the two approaches could be confirmed [9].

Player type models could be of practical use for researchers, game developers and publishers. They could be used for planning new or adapting existing games to target audiences for improving the player experience and facilitating long-term engagement with the games. However, planning, developing and publishing a game is a huge effort. Although it is intriguing to use player type models for game development, we need to be sure they can actually predict player experience.

Although some player type models have been evaluated in terms of psychometric properties (factor structure, stability and reliability [10, 11]), to the best of our knowledge it has not been empirically tested yet, whether or not player types can significantly predict player experience. By utilizing the frequently used and researched (e.g., in [7, 12]) player type model *BrainHex* [13, 14] for the personalization of a mobile location-based persuasive game, we aim to fill this gap and to shed light onto the following research question:

Do player types significantly and reliably predict player experience?

If they do so, they could be an effective tool for the personalization of games. Personalized games could adapt to the player's gaming preferences and would therefore create a better player experience than one-size-fits-all games. To answer this research question, we conducted a field study with 51 participants. We chose two player types within the BrainHex player type model and created two game missions

[2] There is a general difference between trait and type approaches: Type models classify people along fixed categories, whereas trait models describe individual differences on continuous dimensions. For psychometric reasons, we treat the player types as continuous dimensions, and therefore as a trait approach.

with game mechanics tailored to these player types. One player type and the according mission are called *Mastermind,* the other *Seeker*. Both missions were implemented as part of a location-based game prototype. See Table 1 for a short description of the player types and how they were used to create game missions.

Table 1. Overview of the player types investigated in the study and how these player types were used to tailor game missions.

Player Type	**Mastermind**	**Seeker**
Description of player type	Players who enjoy solving puzzles	Players who enjoy exploring unknown areas
Corresponding game mechanic	A “crack the code” activity	Uncovering unknown areas

Prior to the field study, we conducted two online studies (n_1 = 592, n_2 = 243) six months apart to reveal which are the two most represented player types (Mastermind and Seeker). We chose these two most represented ones to investigate in the field study. Furthermore, we use the player type scores that we assessed as predictors of player experience in our field study.

We contribute to personalized systems and games user research with the first work empirically investigating whether player type models—as a specific appearance of personality traits—can be a valid approach to guide the design of more appealing games. Our results show that this is not (yet) the case, as player types in this state cannot significantly predict player experience. We outline how player type models could be improved.

2 Player Type Models – Theory and Practice

In this section we present an overview of previous research relevant to our work. In general, there is a long tradition in Human-Computer Interaction (HCI) to adapt interactive systems and services for various user groups [15], using different factors including personality traits, age, gender, and other stable characteristics [16]. In game user research (GUR), player type models have been proposed in previous research [4] to classify players according to their preferences for specific game mechanics.

One of the oldest and most frequently used player type models is the one by Bartle [17] and its further developments [18]. Bartle identified four player types (*Achiever*, *Explorer*, *Socializer*, and *Killer*), analyzing players of Multi User Dungeons (MUDs) regarding what they wanted out of a MUD. Despite its high prevalence, Bartle’s player type model has several shortcomings: Bartle proposed that each player has some particular overall preference for one of the types (making them mutually exclusive) and did not empirically test the model on independency of the types or on psychometric quality criteria.

Yee [10, 19] aimed to fill this gap by using a factor analytic approach of questions based on Bartle’s player types. His analysis identified three main components (with ten subcomponents) of player motivation with weak correlations: *Achievement* (advancement, mechanics, competition), *Social* (socializing, relationship, teamwork), and *Immersion* (discovery, role-playing, customization, escapism). Like Bartle's model, Yee's components have a limited focus on one specific game type, Massively Multiplayer Online Role-Playing Games (MMORPGs), therefore it is probably not suitable for a broad range of game genres. Furthermore, the predictive validity of this model has not been investigated.

A wider perspective regarding game types is included in the first Demographic Game Design model (DGD1) [20], which is an adoption of the Myers-Briggs type indicator (MBTI) [21] to games. The MBTI includes 16 different personality types, which are combinations of four dichotomous preferences (intuition and sensing, perception and judging, feeling and thinking, introversion and extroversion). The four player styles *Conqueror*, *Manager*, *Wanderer*, and *Participant* are proposed in the DGD1. This model is qualitatively supported by a series of case studies. Besides player styles, the studies related to the DGD1 investigates hardcore and casual players, which are present in all four player styles. Hardcore players (or more appropriate *hobbyists*) play many different games and have a higher game literacy. In the second Demographic Game Design model (DGD2) [5] the hardcore/casual dimension, as well as different skill sets and the preference for single and multiplayer is explored in more detail. Although providing valuable insights in player characteristics, both DGD1 and DGD2 are based on a pre-existing psychometric model (MBTI) that is not focused on games and the authors [5, 20] report issues with used methodologies and data collections.

Emerging from an empirical evaluation of a health game for younger adults, Xu et al. [22] developed five player types: *Achievers*, *Active Buddies*, *Social Experience Seekers*, *Team Players* and *Freeloaders*. These player types include both, motivational and behavioral factors. However, these player types have not been empirically investigated regarding their validity to personalize games.

For personalizing gamification mechanisms of a university-level engineering course, Barata et al. [23] relate preferences for gamification mechanisms to student types: *Achievers*, *Regular Students*, *Halfhearted Student*s and *Underachievers*. A user type model related to gamified systems was proposed by Marczewski [24]. He proposes *Disruptors*, *Free Spirits*, *Achievers*, *Players*, *Socializers*, and *Philanthropists*. These types differ in the degree to which they can be motivated by either intrinsic (e.g., self-realization) or extrinsic (e.g., rewards) motivational factors. However, these models focus on gamified systems, not on games and are not empirically validated.

An attempt to use player types in a persuasive game to promote healthy eating was performed by Orji et al. [25]. They analyzed the receptiveness of seven player types of the BrainHex model (described below) to ten persuasive strategies (e.g., cooperation). Based on their findings, the researchers suggest which persuasive strategies are most suitable for specific gamer types. For example, the player types Achiever and Socializer are receptive to cooperative elements in the game, which is why this strategy could be applied in a persuasive game personalized to these player types. However, they did not empirically verify the validity of their suggestions.

The recent BrainHex model [13, 14] was developed considering previous player typologies. It is a promising approach, supplementing existing research with a more diverse array of player types and it has been used in a number of recent studies (e.g., [9, 12, 25]). The authors introduced seven types:

- Seeker (motivated by interest, curiosity about the game world and moments of wonder),
- Survivor (enjoys fear and terror),
- Daredevil (enjoys the thrill of the chase, risk taking and playing on the edge),
- Mastermind (enjoys puzzles, problems that require strategy to overcome, and making the most efficient decisions),
- Conqueror (challenge-oriented, enjoys struggling against adversity, defeating impossibly difficult foes, and beating other players),
- Socializer (enjoys hanging around with people they trust, talking to them, and helping them), and
- Achiever (goal-oriented, motivated by long-term achievements).

The authors stress the difference between skill-oriented archetypes (*Conqueror*, *Daredevil* and *Mastermind*), aesthetic-oriented archetypes (*Survivor*, *Socializer* and *Seeker*), as well as one goal-oriented archetype (*Achiever*). The authors claim that the archetypes can be used for designing with a specific target group in mind by focusing on gameplay elements, which the target group would find engaging.

The corresponding BrainHex questionnaire assesses the players' dominant gamer type (primary type) and sub-types. The questionnaire consists of 21 questions (e.g., "*Working out how to crack a challenging puzzle"* for the *Mastermind* player type) that have to be rated on a 5-point Likert scale ranging from *"I love it!"* to *"I hate it!"*. For each of the seven player types, participants have to rate three statements. Additionally, participants have to rank seven other statements (e.g., "*A moment of jaw-dropping wonder or beauty*" for the *Seeker* player type) from worst to best. The psychometric properties of the BrainHex questionnaire have recently been investigated [11]: the factor structure of BrainHex could only partly be confirmed, reliability coefficients range from .68 to .78 and stability coefficients from .40 to .70.

Player type models have been widely adopted [4], and although studies [10, 11] provide knowledge on the psychometric quality of player type models, so far—to the best of our knowledge—no empirical study has been conducted showing that player types could actually significantly predict player experience. This is a prerequisite for player type models to be used in a practical and meaningful way in game design and development.

There are two possibilities when player type models can be used: First, we can assess the distribution of player types in the target audience and base game design decisions (such as the use of game mechanics) on these distributions. Second, we can use player type models for personalization during the game and adapt game mechanics to the individual players at runtime (which is also called adaptive games).

For both ways, the reliance on a player type model has far-reaching consequences: We have to be sure that these design decisions have a positive and meaningful impact on how users perceive and interact with the game. It is important to know whether player type models can usefully guide game design and whether researchers, game designers and developers should take the effort to base their game concepts and strategies on player types.

3 Method

To answer the research question, whether player types can significantly and reliably predict player experience, we conducted a field study (n = 51) with a functional game prototype that had two missions.

Prior to the field study, we assessed participants' scores of the BrainHex player types in two online studies ($n_1 = 592$, $n_2 = 243$), which were conducted six months apart. We hypothesize that the high dropout from online study I to online study II is because of the large time interval between the two studies. We recruited participants for the field study from the pool of participants that completed online study I and II. We recruited all participants that indicated they were willing to participate in a follow-up study at the end of online study II.

As it is not feasible to investigate all seven player types in one controlled study, we decided to empirically investigate two player types. We chose the two player types that were most dominant in the first online study: Mastermind and Seeker. Additionally, Mastermind is a skill-oriented archetype and Seeker is a goal-oriented archetype, which led us to the hypotheses that game mechanics based on these types actually vary in their appeal to different players.

Therefore, we created a location-based game prototype with two according missions: one tailored to the Mastermind player type and one tailored to the Seeker player type. We treated these two BrainHex player type scores for Mastermind and Seeker as predictor variables that we relate to player experience (in two missions) as outcome variables.

For our studies we did not use the participants' assigned primary player type (e.g., either Mastermind or Seeker). Instead, we included both player types scores (ranging from 1 to 5) of Mastermind and Seeker into analyses. In line with this, we did not group people into two groups for Mastermind and Seeker player types. In the field study, each participant was asked to play both, the Seeker and Mastermind mission in a counterbalanced order.

We used path analysis[3] to predict player experience by BrainHex scores for Mastermind and Seeker in both missions. We did not model the player types as a latent variable and only used aggregated scales as observed variables, as our sample size was not large enough for a full structural equation modeling approach.

We investigate the following predictor-outcome relations:

1) Player type scores for player experience in congruent missions (e.g., Seeker player type score and Seeker mission player experience),
2) Player type scores for player experience in incongruent missions (e.g., Seeker player type score and Mastermind mission player experience).

If the BrainHex player types significantly predict player experience, the strengths of associations for congruent relations should be high and significant and the strengths of associations for incongruent relations should be low and not significant. We further were interested if the BrainHex player type scores could reliably predict player experience. Therefore, we assessed these scores from the same people at two

[3] We used the *lavaaan* package within the R statistical computing software.

different time points (in the two online studies). This allows us to relate the player type scores from both time points to player experience in the field study.

As an incentive for participation, online study participants could enter a raffle for Amazon gift certificates. Participants in the field study received a voucher valid for various shops. To ensure validity of the results, the study was conducted double-blind: neither the participants nor the study facilitator knew about the real aim of the study, i.e., if player type scores could significantly predict player experience in corresponding missions. Both were informed that the study investigates the user experience of a newly developed mobile game. The facilitator did not know the participants' BrainHex scores. At the end, participants were asked what they thought that the study was about. No participant indicated that he or she made the connection to the player type assessments in the online studies.

In the following section, we first describe the location-based game prototype. Then the predictor variables (the BrainHex scores assessed in two subsequent online studies) are described. Afterwards, we present how we assessed the player experience variables.

3.1 Game Prototype

We designed a location-based game prototype for smartphones. The prototype is a native Android application created with Unity 3D, deployed on a Motorola Moto G2. In the game, the player receives missions from a fictional research company that discovered an alternative version of our world. Through the missions, players are able to collect information about this alternative reality. Navigation in the game is possible through walking.

In the Seeker mission (Figure 1; top) players are primarily encouraged to explore unknown territory. The goal of the mission is motivated through the following incentive: players are shown a strongly distorted image, which represents a view into the alternative reality. It is the goal of the game to reduce the distortion. To do this, players have to physically move to specific sectors, which are shown on a map. The game map overlay shown on the mobile phone consists of sectors that are nearly opaque. When players enter one of those sectors or interact with it, the sector becomes transparent and the map information underneath becomes visible. The specific mission-related sectors are indicated by blue color. In these sectors, players have to perform an action called "scanning" ("Scan" is a button in the interface). With each scan of one of the blue sectors, the image becomes slightly clearer. After finding three quest-related sectors, the image appears without any distortion and shows an alternate version of a known place (e.g., known architecture in the vicinity of the player, but modified in color and shape in comparison to the original version).

The Mastermind mission (Figure 1; bottom) is about a puzzle-solving activity based on characteristics of the board game *Mastermind*[4]. The design combines physical activity with deductive reasoning. Within the game, players are confronted with the challenge to find a correct color combination to gain further intelligence about the alternative reality that was discovered by the research company. Our version

[4] https://boardgamegeek.com/boardgame/2392/mastermind

of the game works with three different colors (orange, purple, and turquoise) that have to be associated with three color slots presented on the mobile phone display. Players have to derive which color fits a specific color slot. The order of the colors is vital to unlock the code. Three sectors on the game map represent the three positions of the code input points. Players have to walk to one of the locations and interact with the mobile phone interface in order to change the color of a sector.

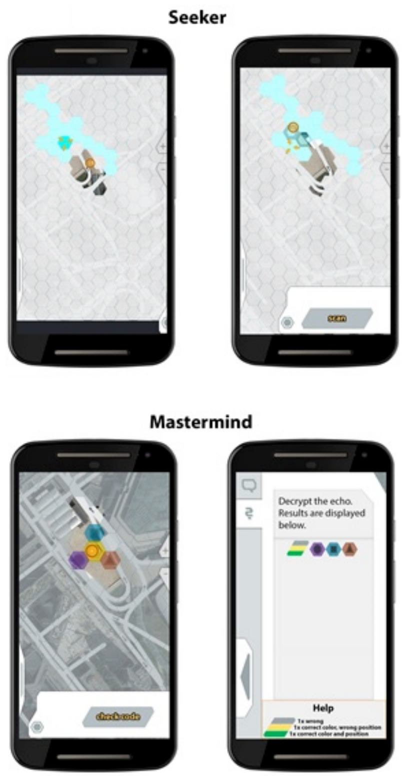

Fig. 1. Location-based game prototype with the Seeker (top) and the Mastermind mission (bottom). In the Seeker mission, players have to explore unknown areas, in the Mastermind mission, players have to solve a puzzle.

To check whether the chosen code is correct, the players have to enter the sector in the middle of the code input points and press the “Check Code” button. Afterwards, players receive feedback whether the entered code is correct or not. The interface indicates when the colors of the sectors are on the correct position (green), on the wrong position (yellow) or when both color and position are wrong (gray). However, the sequence of the feedback is not connected to the order of the code sectors, which increases the required deductive reasoning effort from the player to solve the puzzle.

Figure 2 shows the outdoor setting of the field study for the Mastermind mission. On the ground, there are indications of the sectors from which participants had to move to other sectors. The participant is standing in the middle sector, in which the “Check Code” interaction is enabled.

Fig. 2. Outdoor setting of the field study, indicating the sectors shown on the participant’s mobile game map in the Mastermind mission (the colored fields are just for illustrative purposes, participants have not seen them on the floor, only on the mobile phone; proportions of sectors are smaller than in actual game).

To ensure that the game missions represent the corresponding player types as best as possible, we tied the design process strongly to a published approach for *player type driven game development* [26]. According to this approach, the game prototype was iteratively designed and refined by game design experts.

3.2 Predictor Variables: BrainHex Player Type Scores

We assessed the BrainHex player type scores in two subsequent online studies.
Online Study I. The participants of the first online study were recruited from a database of voluntary study participants from Vienna, Austria. The central part was the administration of the questionnaire for assessing the BrainHex player types. We did not only assess the primary player type for each player, but we assessed all scores of the seven player types. Additionally, we collected demographic information. Data of 592 participants was analyzed.
Online Study II. Six months after completing the first online study, the participants were invited to the second online study, which assessed the BrainHex player types (as described above) a second time. We were able to match 239 participants’ responses in online study I with the responses from online study II (51 of them later participated in the field study).

Calculation of BrainHex Scores. We calculated scores for both, Mastermind and Seeker player types based on three items each. Originally, the BrainHex questionnaire contains four items for assessing each player type. Although we assessed all items, we did not include the fourth item for calculating the scores. The available psychometric data [11] shows that the reliability scores of the BrainHex scales are higher without the fourth item. This is because of two reasons: First, the fourth item has a different response format than the other three items. The fourth item has to be ranked, the other three items have to be rated on a 5-point Likert scale. From a psychometric point of view, it is difficult to calculate an overall score for items with different response formats. Second, the actual response to one item should not be influenced by the response to another item—which is not valid for ranked items.

Although available factor analytic data [11] suggests to remove certain items (e.g., item 3 of Mastermind), we needed to assess the predictive validity of the BrainHex scores with at least three items per player type, because using aggregate scales with fewer than three items is not a meaningful approach.

3.3 Outcome Variables: Player Experience in Field Study

One month after completing online study II, participants that participated in both, online study I and II were invited to participate in the field study.

After being introduced to the study, all participants played both missions of the game in a counterbalanced order. To ensure that all participants were playing the missions more or less for the same time, we ended each game mission after roughly half an hour. The overall study duration per participant was about 1 to 1.5 hours (including the post-assessment). We registered if participants had solved the mission (within the provided time) and if they needed help.

After each mission, we assessed participants' player experience (fun, liking, perceived difficulty, the general preference of this kind of mission and their emotional valence, arousal and dominance). We assessed experiential, as well as emotional aspects of player experience.

The experiential aspects of player experience (fun, liking, perceived difficulty, general preference) were assessed with statements that had to be rated on a 7-point Likert scale (e.g., "This mission was fun"). These factors can be assessed with different methods (e.g., psychophysiological measures, questionnaires) [27]. For this study, we chose variables that are often assessed in digital games (fun, liking) or were considered important for the study purposes (difficulty). We did not use standard scales such as the *Game Engagement Questionnaire* [28]. These scales are typically not designed in a way to assess player experience for single missions in a game, but are focused on overall game immersion. Overall game immersion was not central to our research question, thus these scales were not suitable for our study. Furthermore, we analysed each single item separately in our path model, therefore we did not introduce a new scale that had to be validated before being used. We consider our items (e.g., "This mission was fun" to assess "fun") to be face valid.

The rather emotional aspects of player experience (valence, arousal and dominance) were assessed with the validated and frequently used pictorial scales from the *Self-Assessment Manikins* [29], an approach that builds on the well-researched circumplex model of emotions by Russel [30].

After both missions were completed, we additionally assessed the overall player experience (e.g., "The game was fun") and related factors (usability, subjective technical performance of prototype), mainly for control purposes.

3.4 Participants in Field Study and Distribution of Player Type Scores

Overall 51 people participated in the field study, 18 of them were female (35%). Participants' age ranged from 24 to 78, the mean was 39 years. Most of our study participants had at least some experience with video games. Three participants (6%) never play video games (neither on mobile, console nor PC), two (4%) play seldom, 15 (30%) play sometimes, 14 (27%) play at least once a week and 17 (33%) play video games every day.

Figure 3 shows the distribution of participants' scores on Mastermind and Seeker player types for the first assessment (S1, M1) and the second assessment (S2, M2). The distributions appear quite similar. The Pearson correlation between Mastermind and Seeker in the first assessment is .29 and in the second assessment is .33, which can be considered low to medium.

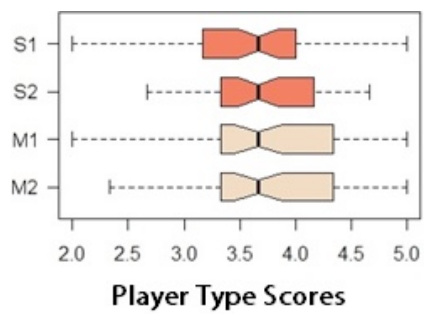

Fig. 3. Distribution of Seeker and Mastermind player type scores across the field study participants for the first (S1, M1) and second online assessment (S2, M2).

4 Results

First, we briefly present results regarding the overall player experience and we check for significant differences between player experience variables for the single missions. To answer our research question, we relate the BrainHex scores (assessed at two points in time) to actual player experience.

4.1 Overall Player Experience and Difference between Game Missions

To understand the general perception of the prototype, this section presents the overall player experience assessed in the field study. On the 7-point Likert scale that was used to rate the different player experience variables (e.g., fun), 1 is "Total Disagreement" and 7 is "Total Agreement". In the following, we always present mean ratings.

Participants rather thought the game was fun (5.02). They rather liked it (4.88) and considered the overall difficulty as appropriate (5). Their preference for this kind of video game was rated neutral (4.12). They highly enjoyed the physical activity in the game (5.57) and rated the game story as neutral (4.18). Considering usability and perceived technical performance, they thought it was rather usable (5.01) and that it was rather working well in technical terms (4.67). In open-ended responses, 35 (67%) participants explicitly called the game "good" or "very good". This shows a rather positive picture of the game prototype and supports the methodological robustness of the study.

To determine whether the missions Mastermind and Seeker are overall (independent of player type scores) perceived in the same manner, we use paired t-tests to check for differences in means: There are no significant differences in liking [$t(50) = -1.97$, $p = .054$], difficulty [$t(50)= -1.26$, $p = .25$] and general preference [$t(49) = -0.86$, $p = .39$]. There is a significant difference in fun [$t(50) = -2.0163$, $p = .049$], with Seeker having a slightly lower mean (4.63) than Mastermind (5.04). 17 (33%) players needed help with the Seeker mission and 14 (27%) players needed help with the Mastermind mission.

4.2 Predictive Power of Player Types

To answer our research question whether player type scores can significantly predict player experience, we calculate a path analysis with Mastermind and Seeker player type scores as predictor variables (assessed twice, six months apart) and the experiential and emotional player experience variables as outcome variables. Table 2 shows the result of the path analysis. The upper half of the table shows the relationships between player type scores and game mission experience for the first assessment of the scores, the lower half for second assessment of the scores. The table shows both congruent conditions (e.g., Seeker score related to player experience in Seeker mission) and incongruent conditions (e.g., Seeker score related to player experience in Mastermind mission).

Table 2. Path analysis on the relationship between scores of Mastermind and Seeker player types (at two different time points for the same people) and experiential and emotional measures of player experience in congruent (e.g. Mastermind player type score and Mastermind mission experience) and incongruent (e.g. Mastermind player type score and Seeker mission experience) conditions.

Condition	*Parameter Estimate*	*Standardized*	*p*
Congruent: Seeker score 1 & Seeker mission experience	"This mission was fun"	−.261	.476
	"I liked the mission"	.174	.660

	"This mission was difficult"	.005	.976
	"This is the kind of mission that I generally prefer in games"	−.167	.481
	Valence	.401	.118
	Arousal	−.255	.148
	Dominance	.148	.435
Incongruent: Mastermind score 1 & Seeker mission experience	"This mission was fun"	.188	.654
	"I liked the mission"	−.018	.968
	"This mission is difficult"	−.027	.890
	"This is the kind of mission that I generally prefer in games"	−.123	.651
	Valence	−.128	.665
	Arousal	−.032	.873
	Dominance	.231	.289
Incongruent: Seeker score 1 & Mastermind mission experience	"This mission was fun"	−.280	.322
	"I liked the mission"	.493	.093
	"This mission is difficult"	.327	.127
	"This is the kind of mission that I generally prefer in games"	−.061	.779
	Valence	−.089	.767
	Arousal	.307	.054
	Dominance	−.030	.870
Congruent: Mastermind score 1 & Mastermind mission experience	"This mission was fun"	−.129	.690
	"I liked the mission"	.094	.780
	"This mission is difficult"	.051	.834
	"This is the kind of mission that I generally prefer in games"	.097	.697
	Valence	.184	.592
	Arousal	.092	.615
	Dominance	−.350	.093
Congruent: Seeker score 2 & Seeker mission experience	"This mission was fun"	−.272	.439
	"I liked the mission"	−.142	.709
	"This mission is difficult"	.239	.139
	"This is the kind of mission that I generally prefer in games"	−.245	.280
	Valence	.332	.177
	Arousal	−.076	.654
	Dominance	.079	.665
Incongruent: Mastermind score 2 & Seeker mission experience	"This mission was fun"	.079	.845
	"I liked the mission"	−.359	.411
	"This mission is difficult"	.052	.781
	"This is the kind of mission that I generally prefer in games"	.151	.564
	Valence	−.159	.574
	Arousal	−.043	.825
	Dominance	.016	.941
Incongruent: Seeker score 2 & Mastermind mission experience	"This mission was fun"	.037	.891
	"I liked the mission"	.195	.487
	"This mission is difficult"	.356	.083
	"This is the kind of mission that I generally prefer in games"	−.019	.929
	Valence	.048	.868

	Arousal	.468	.002
	Dominance	−.142	.415
Congruent: Mastermind score 2 & Mastermind mission experience	"This mission was fun"	.217	.486
	"I liked the mission"	−.296	.361
	"This mission is difficult"	.025	.916
	"This is the kind of mission that I generally prefer in games"	−.094	.694
	Valence	.294	.374
	Arousal	.123	.485
	Dominance	−.114	.571

If the player type scores—according to our hypotheses—are able to significantly predict player experience in the according missions, Seeker player type scores should significantly predict player experience in the Seeker mission. To allow for a reliable prediction, this should be true for both points in time when the Seeker scores have been assessed. Equally, Mastermind scores should predict player experience in the Mastermind missions. However, for the player types to be distinctive, Seeker player type scores should not significantly predict player experience in the Mastermind mission. Again, the same applies to the player type score for Seeker, which should not significantly predict player experience for the Mastermind mission.

The actual results regarding the predictive power of the player types show two things:

1. The congruent player type scores did not significantly predict player experience in the according missions (e.g., Mastermind scores did not significantly predict the experienced fun in the Mastermind mission). On the contrary, in one case (Seeker score 2 & Mastermind mission experience) the incongruent scores did significantly predict the player experience.

2. There is no clear pattern about which scores (from online study I or II) did predict player experience better.

5 Discussion

Player types can be operationalized as a specific appearance of personality models. Personality and player type models should allow for the explanation of individual differences in player behavior and experience. We investigated whether player types could significantly predict player experience to decide whether personalization of a mobile game according to a player type model could be a meaningful approach. There is recent interest and effort in using player type models for game design [4]. This is especially true for personalizing persuasive games [6, 7]. Player type models state that different players prefer different game mechanics (e.g., some players enjoy collecting things, whereas others rather enjoy solving puzzles). Player type models could be of practical use for game development projects. Nevertheless, before they are applied in game design, we need to assure their predictive power in terms of player experience.

This has—to the best of our knowledge—not been examined before this study. We chose the recent BrainHex player type model and tailored two missions of a location-based game along to the two player types Mastermind and Seeker. A sample of 51 participants played both missions in a counterbalanced order. After each mission, we asked for the participants' subjective player experience. We associated the player experience of the two missions to the BrainHex scores of the according player types Mastermind and Seeker that we assessed two times before online in an interval of six months.

Our results show that the BrainHex player type model is weak in predicting player experience of personalized game dynamics. That means, higher Seeker player type scores were not significantly associated with a higher player experience in the Seeker mission. The same applies for the Mastermind player type and Mastermind mission. Furthermore, one time the incongruent player type was a better predictor for player experience than the congruent player type (e.g., sometimes a higher Mastermind score was significantly associated to a higher player experience in the Seeker mission).

We discuss our results based on three aspects: a) player type models as traits, b) independence of player types, and c) determinants of player experience. In the following, we elaborate on these areas.

5.1 Player Type Models as Traits

A prerequisite for the meaningful use of player type models for design and therefore a central question is whether player preference for certain game dynamics can be indicative for an underlying trait model or whether this preference is more depending on situational factors, such as mood or emotional state.

A point that would support considering the BrainHex as a trait model is that there are some relations to traits, with the Big Five [9] and the Myers-Briggs personality types [21]. Further research and development activities related to player types (not only limited to the BrainHex player type model) will have to face this issue and must conceptualize the player types as a trait model as a basis for valid design decisions.

5.2 Independence of Player Types

Besides the question whether player types can be considered as traits, there are other underlying assumptions of the player types that have not been tested yet. To which degree do the player types influence each other? Can all player types be considered as equal regarding their impact on game design?

Our results might imply that the two player types that we investigated could not be distinguishable enough to create unique player experiences. To allow for meaningful cause-effect statements from player type to game dynamics the player types have to be both, exhaustive but also as non-redundant and non-overlapping as possible. At the same time, a methodological tidy conceptualization of player types does not rely on categorizing players into just one type, but considers more fine-grained player (type) profiles.

5.3 Determinants of Player Experience

Not only the conceptualization of the player types themselves is important, how we assess the association between player types and player experience is also crucial: Player experience is a multidimensional construct [27]. Like in any other construct that relies on subjective perception and evaluation, player experience is influenced by several factors beyond the pure gameplay. People have different perceptions and experiences. Further, their player experience is different, even when playing the same game. The question is to what extent the player experience is influenced by the game itself and to what extent it is influenced by other factors. Other determining factors could for example be previous experiences with similar games, situational factors or other personal characteristics beyond player types. In addition, unsystematic measurement errors common in HCI studies have to be considered, too.

5.4 Limitations of this study

The validity of our work is limited by a drawback that applies to all player type models in general: There are no empirically-driven design guidelines on how to translate player types into meaningful game designs. Although a first effort was made by Lankes et al. [26], this is still a "black box"-process. Based on the player types, there are different ways to design tailored game dynamics. These different possibilities could have affected the results and were not explored in this study. However, we chose mission designs that were as close as possible to the definitions of the player types Mastermind and Seeker.

For reasons of feasibility, our study only investigated two player types that were most prevalent in online studies and are conceptually very different: Mastermind and Seeker. Future studies will have to consider other player types besides these two as well. Possible effects of a combination of several player types, e.g., a combination of Mastermind and Socializer (collaborative puzzle-solving) should also be explored. Furthermore, our results are not generalizable to all kinds of game genres. Further research will have to investigate how player type models work for different games and genres and should also include other player type models (e.g., the player motivations model by Yee [10]).

6 From Player Type Models To Player Personalities

Building on the presented work we suggest the following research agenda for improved player type models. We imagine the development of *player personalities* that can reliably predict player experience: a player trait model with independent and stable traits that covers a broad range of game dynamics. The player personalities should give clear implications and guidelines for designing digital games in several genres.

As a first step, researchers and practitioners should move from player types to player profiles. Using player type models should deviate from stereotyped thinking (e.g., by assigning only the dominant player type), and allow for a deep and fine-grained understanding of players (e.g., by considering detailed player type profiles). Next, the player personalities need to cover a broad variety of game dynamics (exhaustiveness). The preference for game dynamics should then be related to human traits in empirical studies to find the best way to operationalize the player personalities.

In studies with large samples, we have to identify patterns between human traits and game dynamics and derive player personalities. With factor analytic procedures, we have to check whether these player personalities are independent from each other (i.e., non-redundancy). This is similar to Yee's approach [10], but should be generalizable beyond Massively Multiplayer Online Role-Playing Games.

In long-term studies, we have to investigate whether these empirically-grounded, independent player types are stable over time. Furthermore, a critical research question to be explored is the relationship between personalization of a persuasive game and long-term usage of this game.

7 Conclusion

Player type models are a promising and recently often used and discussed approach for the personalization of games. Until now, it has—to the best of our knowledge—never been investigated whether player types are actually linked to player experience. Our study of the personalization of a location-based game along two player types (Mastermind and Seeker) of the BrainHex player type model did not show the expected results: player types could not significantly and reliably predict player experience for personalized missions. We conclude that there is still conceptual and empirical work left to ensure the validity of player type models. Player type models should evolve to player personalities and should be improved based on the following criteria: relation to traits, exhaustiveness and non-redundancy.

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References

1. Susi, T., Johannesson, M., Backlund, P.: Serious games – An overview. (2007).
2. Bogost, I.: Persuasive games: The expressive power of videogames. Mit Press (2007).
3. Busch, M., Mattheiss, E., Orji, R., Marczewski, A., Hochleitner, W., Lankes, M., Nacke, L.E., Tscheligi, M.: Personalization in Serious and Persuasive Games and Gamified Interactions. Proceedings of the 2015 Annual Symposium on Computer-Human Interaction in Play. pp. 811–816. ACM Press, New York, USA (2015).
4. Hamari, J., Tuunanen, J.: Player types: A meta-synthesis. Transactions of the Digital

Games Research Association (2014).
5. Bateman, C., Lowenhaupt, R., Nacke, L.: Player typology in theory and practice. Proceedings of DiGRA. pp. 1–24 (2011).
6. Millonig, A., Mitgutsch, K.: Playful Mobility Choices: Motivating informed mobility decision making by applying game mechanics. ICST Trans. Ambient Syst. 1, e3 (2014).
7. Orji, R., Mandryk, R.L., Vassileva, J., Gerling, K.M.: Tailoring persuasive health games to gamer type. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. pp. 2467–2476. ACM Press, New York, USA (2013).
8. Costa, P., McCrae, R.: Normal personality assessment in clinical practice: The NEO Personality Inventory. Psychol. Assess. 4, 5–13 (1992).
9. Zeigler-Hill, V., Monica, S.: The HEXACO model of personality and video game preferences. Entertain. Comput. 11, 21–26 (2015).
10. Yee, N., Ducheneaut, N., Nelson, L.: Online gaming motivations scale: development and validation. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. pp. 2803–2806. , New York (2012).
11. Busch, M., Mattheiss, E., Orji, R., Fröhlich, P., Lankes, M., Tscheligi, M.: Player Type Models – Towards Empirical Validation. Extended Abstract Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (2016).
12. Birk, M., Toker, D., Mandryk, R., Conati, C.: Modeling Motivation in a Social Network Game using Player-Centric Traits and Personality Traits. User Modeling, Adaptation and Personalization. pp. 18–30. Springer (2015).
13. Nacke, L., Bateman, C., Mandryk, R.: BrainHex: Preliminary results from a neurobiological gamer typology survey. ICEC. 288–293 (2011).
14. Nacke, L., Bateman, C., Mandryk, R.: BrainHex: A neurobiological gamer typology survey. Entertain. Comput. 5, 55–62 (2014).
15. Egan, D.: Individual differences in human-computer interaction. In: Helander, M. (ed.) Handbook of Human-computer Interaction. pp. 543–568. Elsevier Science Publishers, Amsterdam (1988).
16. Dillon, A., Watson, C.: User analysis in HCI: the historical lesson from individual differences research. 619–637 (1996).
17. Bartle, R.: Hearts, clubs, diamonds, spades: Players who suit MUDs. J. MUD Res. 1 (1999).
18. Bartle, R.: Virtual Worlds: Why People Play. Massively Mult. game Dev. 2, 3–18 (2005).
19. Yee, N.: Motivations for play in online games. Cyberpsychol. Behav. 9, 772–775 (2006).
20. Bateman, C., Boon, R.: 21st Century Game Design (Game Development Series). Charles River Media, Inc., Rockland, MA, USA (2005).
21. Myers, I.B.: Myers-Briggs Type Indicator. Consulting Psychologists Press, Inc., Palo Alto, CA (1977).
22. Xu, Y., Poole, E.S., Miller, A.D., Eiriksdottir, E., Kestranek, D., Catrambone, R., Mynatt, E.D.: This is not a one-horse race: understanding player types in multiplayer pervasive health games for youth. Proceedings of the ACM 2012 conference on computer supported cooperative work. p. 843. ACM Press, New York, New York, USA (2012).
23. Barata, G., Gama, S.: Relating gaming habits with student performance in a gamified learning experience. Proceedings of the first ACM SIGCHI annual symposium on Computer-human interaction in play. pp. 17–25. ACM (2014).
24. Marczewski, A.: User Types. Even Ninja Monkeys Like to Play: Gamification, Game Thinking and Motivational Design. pp. 65–80. Create Space Independen Publishing Platform (2015).
25. Orji, R., Vassileva, J., Mandryk, R.L.: Modeling the efficacy of persuasive strategies for different gamer types in serious games for health. User Model. User-adapt. Interact. 1–46 (2014).
26. Lankes, M., Hochleitner, W., Rammer, D., Busch, M., Mattheiss, E., Tscheligi, M.: From

Classes to Mechanics: Player Type Driven Persuasive Game Development. Proceedings of the 2015 Annual Symposium on Computer-Human Interaction in Play. pp. 595–600. ACM (2015).
27. Drachen, A., Nacke, L.E., Yannakakis, G., Pedersen, A.L.: Correlation between heart rate, electrodermal activity and player experience in first-person shooter games. Proceedings of the 5th ACM SIGGRAPH Symposium on Video Games. pp. 49–54. ACM (2010).
28. Brockmyer, J.H., Fox, C.M., Curtiss, K. a, Mcbroom, E., Burkhart, K.M., Pidruzny, J.N.: The development of the Game Engagement Questionnaire: A measure of engagement in video game-playing. J. Exp. Soc. Psychol. 45, 624–634 (2009).
29. Bradley, M.M., Lang, P.J.: Measuring emotion: The self-assessment manikin and the semantic differential. J. Behav. Ther. Exp. Psychiatry. 25, 49–59 (1994).
30. Russell, J.A.: A circumplex model of affect. J. Pers. Soc. Psychol. 39, 1161–1178 (1980).