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Modeling the Player, Learner and Personality: Independency of the Models of Bartle, Kolb and NEO-FFI (Big5) and the Implications for Game Based Learning

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Abstract: For adaptation and personalization of game play sophisticated player models and learner models are used in game-based learning environments. Thus, the game flow can be optimized to increase efficiency and effectiveness of gaming and learning in parallel. In the field of gaming still the Bartle model is commonly used due to its simplicity and good mapping to game scenarios, for learning the Learning Style Inventory from Kolb or Index of Learning Styles by Felder and Silverman are well known. For personality traits the NEO-FFI (Big5) model is widely accepted. When designing games it is always a challenge to assess one player's profile characteristics properly in all three models (player/learner/personality). Still, it is valuable to collect information to refine the models continuously to adapt the game experience precisely to a player's models. To reduce the effort and amount of dimensions and questionnaires a player might have to fill out, we proved the hypothesis that both, Learning Style Inventory and Bartle Player Types could be predicted by knowing the personality traits based on NEO-FFI. Thus we investigated the statistical correlations among the models by collecting answers to the questionnaires of Bartle Test, Kolb LSI 3.1 and BFI-K (short version of NEO-FFI). The study was conducted in spring 2012 with six school classes of grade 9 (12-14year old students) in two different secondary schools in Germany. 72 students participated in the study which was offered optionally after the use of a game-based learning tool for peer learning. We present the results, statistics and correlations among the models as well as the interdependencies with the student's level of proficiency and their social connectedness. In conclusion, the evaluation proved the independency of the models and the validity of the dimensions. Still, especially for all of the playing style preferences of Bartle's model significant correlations with some of the analyzed other questionnaire items could be found. As no predictions of learning style preferences is possible on the basis of this studies data, the final recommendation for the development of game-based learning application concludes that separate modeling for the adaptation game flow (playing) and learn flow (learning) is still necessary.

Keywords: Player Modeling, Bartle Test, Learning Style, Personality, Big5

1 Introduction and motivation

During the design phase of a computer game decisions have to be made, how the preferences of the user, his playing behavior, gained abilities and his personal characteristics are measured and represented in a model. Usually different types of measures are kept and updated in separate models for style of game play behavior (player model), skills and abilities achieved and proofed during game play (learner model) and more static characteristics of the player's personality (personality model).

To keep a player immersed into the computer game a continuing measurement and update of the model dimensions is necessary to refine the knowledge about players' preferences and his changing (growing) set of game-related skills. Thus, the adaptation can choose suitable alternatives of game content and/or learning content and balances the difficulty of challenges with the players' abilities, well known as maintenance of a flow status (Chen 2007).

Even though several theories and related, empirically validated, models exist to categorize player behavior into player types and learning behavior into learning styles, they all have a natural common aspect: they focus on decisions and behavior *of the person to model*. Concerning such modeling of a person, very sophisticated models exist in psychology that have been refined and empirically proved across manifold cultures and generations. The NEO-FFI (also known as Big-5 model) is a widely accepted model representing a person's personality in five dimensions. Thus, we investigated how well player model characteristics and learning style characteristics of a person can be predicted by measuring mainly the personality traits.

As the NEO-FFI is widely accepted as one of the most precisely models for personality traits it might be possible to establish a standard on how player models are to be build, measured and how game adaptation may use such models then. Likewise the learning styles could be predicted based on the personality characteristics of a person.

To find the dependencies and correlations among the models to predict player type and learning styles from personality traits of a person, we describe in the following sections the used models in more detail, how we setup the study and discuss the results.

2 Related work

2.1 Established models for player modeling, learner modeling and personality modeling

In related work the underlying models are briefly described that are used for modeling and tracking player behavior. Considering the player modeling, Bartle (Bartle 1996) recommends a two-dimensional playing style system: One axis between action-orientation and interaction-orientation and the other between player-orientation and world-orientation. In these four areas of the coordinate system are lying the player styles Socializer (Interacting, Player-oriented), Killer (Acting, Player-oriented), Achiever (Acting, World-oriented) and Explorer (Interacting, World-Oriented). Bartle draws his classification from the analysis of a long and intense discussion of expert players of a specific MUD (Multi User Dungeon) game. Even though these playing style preferences have not been proven to be likewise suitable for other games or game genres, it is still very popular to be used for the mapping of alternate game content or game story variations and the assumed playing style preferences of a player. It can be assumed that this is due to the fact that Bartle first provided a simple model easy to implement and in the same time easy for mapping of alternate game content or game story variations to these playing style preferences:

A *Socializer* (S) is interested in people and communication with them. The game is the environment to get to know people and establish a network of friendship. In difference, *Killers* (K) lurk for the competition and contest with other players. They like to conquer others and downsize their personae. This does not necessarily mean by having death match fights (as the name suggests), but finally Killers feel good if someone else in the game suffers from their actions. The other two playing style preferences are world-oriented. The *Achievers* (A) mainly collect points and enrich their profile and/or character. Thus, they are eager to get all available achievements of a game, but are only interested in interaction or competition with others to reach these aims. The *Explorers* (E) focus on discovering the game world and game mechanics. Consequently they are eager to know the hidden places, the awkward way to solve a puzzle that is only possible due to a game bug and they know the game world map by heart.

To be best of our knowledge no official Bartle test questionnaire has been published, but we corresponded with Erwin S. Andreasen who developed with Brandon Downey the questionnaire for Bartle's playing style preferences and already collected data of more than 200.000 recipients (Andreasen n.d.; Bartle 2004, p.145). The provided questionnaire contains 6 or 7 questions per each of the 6 combinations of two different Bartle playing style preferences. Each of these items containing two possible answers to questions about the participant's preferences. One of the possible choices relates to one of the two playing style preferences associated with the item. The other answering option relates to the second associated style. Thus, for all combinations of all playing style preferences the participant has to make choices which to prefer. In detail the following number of items for each combination is set: S/A: 7, S/E: 6, S/K: 7, E/A: 6, E/K: 7 and K/A: 6. The items sum up to percentages on how much each playing style is preferred by the participant. In total 200% are spread among the four styles, but each style has a maximum of 100% (Andreasen n.d.).

In learning style preferences, several models like the revised version of the Index of Learning Styles (ILS) of Felder and Silverman (Felder & Silverman 1988) or the recent versions of the Learning Style Inventory (LSI) of Kolb and Kolb (2005) are widely used. While the ILS differentiates the four independent dimensions of learning style *Sensing/Intuiting*, *Visual/Verbal*, *Active/Reflective* and *Sequential/Global*, the LSI distinguishes among the two dimensions *Concrete/Abstract* and *Active/Reflective* Learning Style. In comparison, the ILS appears to be more detailed in the number of dimensions and differentiates among perception, provisioning, processing and understanding of the learning content, the LSI in contrast provides a very elaborated and empirically in many disciplines evaluated model of calculating the learning style preferences of participating learners. ILS contains 44 items with 11 questions per dimension allowing participants to choose among two alternate answers. Thus users must decide on each dimension their preferences. In LSI the 12 items allow four answers each that enable participants to choose always the learning style dimension that suits most for them. Thus the LSI appears to be more accurate in measuring the learning style preferences and is focused in the continuing paragraphs. A similar study could be conducted easily with the ILS as well by simply changing the questionnaire parts accordingly.

The main model this article focusses on is the well-established NEO-FFI personality model consisting of the so called *Big Five* dimensions *Openness to experiences*, *Conscientiousness*, *Extraversion*, *Agreeableness* and *Neuroticism* (De Fruyt et al. 2004). Over the years since the 1930th the model and questionnaires measuring the personality in these dimensions have been elaborated and been narrowed down to a short version of the Big Five Inventory (BFI-K) questionnaire that only needs 21 items which measure for each dimension with four of the items the result and have once extra question for the dimension *openness for experiences* for reliability reasons (Rammstedt & John 2005).

2.2 Application of the established models in game-based learning

The described models are applicable for evaluation and selection of the next most suitable game content element (or game scene) in case several alternatives are available for the game engine in a specific game loop that needs to decide which element to load next. Therefore game elements are annotated by game designers with their suitability for the described model dimensions above. If not only one model, but several in parallel are used, weighting factors might be set (statically or dynamically) to decide in which ratio the diverse models' suitability counts. Bartle's playing styles are used to adapt the game quests and appearance to the specific kind of tasks the different styles stand for. Game-based learning components of research projects like 80days (Kickmeier-Rust et al. 2008) or *Storytec* (Mehm 2010) combine learning style annotation of game scenes using the competency-based knowledge space theory (Albert & Lukas 1999) with the playing styles of Bartle by providing annotation possibilities for game authors in an authoring environment for both models and a runtime weighting possibility to influence the selection of game content to be selected next (Mehm et al. 2010). Commercially the usage of learning style or player style models is not widely published, but in several recent game releases or games to be released, the concept of providing the game content and the path through the game scenes (or quests) by adapting to a four playing style model is obvious. In example, the massive multiplayer online role-playing game *WildStar*[1] (to be released in 2013) provides different player experiences of the game very closely related to Bartle's playing styles. Likewise, the collaborative multi-player game *Woodment*[2] uses Bartle's model to adapt the occurrence of game events and content to the playing style preferences of the players whose preferences are tracked during game play and derived from decisions taken in game by the players (Wendel et al. 2010).

2.3 (In)dependency of the models for player type, learning style and personality traits

As the NEO-FFI model consists of five dimensions world-wide accepted as the model for personality of an individual and provides evaluated questionnaires for nearly every language, we focus on the investigation of the predictability of the values in LSI and the Bartle model based on one individual person's values in the NEO-FFI model. If such a correlation and predictability exists a game engine and learning engine of a computer game can adapt game content and learning content based on the NEO-FFI model values of an individual only.

3 Study setup

For the study we translated the questionnaires for the Bartle test and the Kolb LSI 3.1 to German with suitable vocabulary for secondary school class pupil aged 12 to 14. We conducted the study between 21st of March and 3rd of May 2012 in six secondary school classes (9th year) of two different schools in Germany. After the evaluation of an e-learning diagnostic and learning environment in a math class scenario the paper-based questionnaire was handed out to the pupils to fill them at home. All items of the three models were encoded and aggregated as described in the designated publications. The overall scores in the dimensions (4 dimensions for Bartle playing style preferences, 4 dimensions for Kolb's LSI and 5 dimensions for NEO-FFI) where then normalized to have consistent values in the (0,1) interval. Additionally the quality of the data was calculated to track the percentage of missing answers in the items underlying each of the aggregated values for the dimensions. Thus it was possible to leave out users from the data analysis that provided less than 75% of all answers needed to calculate the values for the models' dimensions.

Within one week the class teachers collected the returned questionnaires and returned them for analysis. 74 of the overall 193 pupils returned their validly filled paper survey containing all items for the three models of Bartle's playing style (39 items), Kolb's LSI 3.1 (52 items) and the short version of BFI-K (21 items; sum of all items was 112). In our scenario all 76 participating pupils filled the survey for all items by 87% (71.6% of the pupils filled 100% of the items). After filtering out participants with a lower value than 75% of provided answers for one of the items 72 valid datasets remained for the analysis (22 f/ 50 m).

Additionally to the analysis of the dependency among the three models we used the items collected during the mentioned e-learning environment testing with an electronic questionnaire. We analyzed the correlations of the mentioned three models' dimensions with e.g. the pupils' proficiency level (math course marks) and level of social connectivity with the classmates.

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[1] See NCSoft website of *WildStar* at http://www.wildstar-online.com/ for details

[2] See project website and online demo at http://demos.storytec.de

Table 1: Correlations (Pearson) between the three models' dimensions (Bartle, Kolb LSI and BFI-K). *N*=72, * significance level 0.01 ** significance level 0.05

		Bartle (Achiever)	Bartle (Explorer)	Bartle (Killer)	Bartle (Socializer)	Kolb LSI (Experiencing)	Kolb LSI (Reflecting)	Kolb LSI (Thinking)	Kolb LSI (Doing)	BFI-K (Extraversion)	BFI-K (Agreeableness)	BFI-K (Conscientiousness)	BFI-K (Neuroticism)	BFI-K (Openness)
Bartle (Achiever)	corr.	1	-.260*	-.044	-.510**	.075	.203	.277*	-.049	-.121	-.068	-.218	.033	.021
	sig.		.028	.711	.000	.533	.088	.018	.680	.313	.568	.065	.782	.861
Bartle (Explorer)	corr.	-.260*	1	-.547**	.064	-.114	.108	-.005	.136	-.128	.147	.130	-.122	.137
	sig.	.028		.000	.593	.340	.366	.965	.255	.283	.217	.276	.306	.250
Bartle (Killer)	corr.	-.044	-.547**	1	-.619**	.043	-.141	-.061	-.086	.024	-.202	-.202	.138	-.119
	sig.	.711	.000		.000	.717	.239	.608	.473	.841	.089	.089	.247	.318
Bartle (Socializer)	corr.	-.510**	.064	-.619**	1	-.044	-.096	-.145	.004	.155	.191	.276*	-.107	.007
	sig.	.000	.593	.000		.713	.420	.225	.973	.195	.108	.019	.372	.953
Kolb LSI (Exper.)	corr.	.075	-.114	.043	-.044	1	.315**	.518**	.303**	-.146	.042	.054	.032	-.287*
	sig.	.533	.340	.717	.713		.007	.000	.010	.220	.725	.652	.788	.015
Kolb LSI (Reflecting)	corr.	.203	.108	-.141	-.096	.315**	1	.525**	.456**	-.121	-.172	-.115	.114	.022
	sig.	.088	.366	.239	.420	.007		.000	.000	.312	.148	.337	.338	.855
Kolb LSI (Thinking)	corr.	.277*	-.005	-.061	-.145	.518**	.525**	1	.328**	-.197	.064	.004	.019	-.193
	sig.	.018	.965	.608	.225	.000	.000		.005	.097	.593	.974	.876	.104
Kolb LSI (Doing)	corr.	-.049	.136	-.086	.004	.303**	.456**	.328**	1	.060	-.192	-.062	.148	-.038
	sig.	.680	.255	.473	.973	.010	.000	.005		.618	.106	.603	.216	.749
BFI-K (Extrav.)	corr.	-.121	-.128	.024	.155	-.146	-.121	-.197	.060	1	-.047	-.115	-.116	.097
	sig.	.313	.283	.841	.195	.220	.312	.097	.618		.693	.335	.330	.417
BFI-K (Agreeabl.)	corr.	-.068	.147	-.202	.191	.042	-.172	.064	-.192	-.047	1	.037	-.229	-.015
	sig.	.568	.217	.089	.108	.725	.148	.593	.106	.693		.755	.053	.904
BFI-K (Consc.)	corr.	-.218	.130	-.202	.276*	.054	-.115	.004	-.062	-.115	.037	1	-.327**	.149
	sig.	.065	.276	.089	.019	.652	.337	.974	.603	.335	.755		.005	.211
BFI-K (Neurot.)	corr.	.033	-.122	.138	-.107	.032	.114	.019	.148	-.116	-.229	-.327**	1	.234*
	sig.	.782	.306	.247	.372	.788	.338	.876	.216	.330	.053	.005		.048
BFI-K (Openness)	corr.	.021	.137	-.119	.007	-.287*	.022	-.193	-.038	.097	-.015	.149	.234*	1
	sig.	.861	.250	.318	.953	.015	.855	.104	.749	.417	.904	.211	.048	

4 Results

As all items of the questionnaire have been scaled to the interval (0,1) the correlations are calculated by Pearson's algorithm for two-side effect. As shown in table 1 all correlations that are significant with an error probability < 0.01 are within the three models. In the results a Bartle *Achiever* is with a correlation of -0.51 not a *Socializer* simultaneously, likewise an *Explorer* correlates negative (-0.547) with *Killers* and *Killers* seem not to be *Socializers* either (-0.619). Within the Kolb LSI all four dimensions correlated significantly positive with each other (correlations between 0.3 and 0.53). The highest values are related to Kolb LSI style *Thinking* (Abstract Conceptualization) predicting *Reflecting* and *Experiencing* with correlations > 0.5. Finally within the BFI-K personality dimensions *Neuroticism* and *Conscientiousness* correlate by -0.327 with each other.

When focusing on the correlations between dimensions of two distinct of the three models we as well consider now the significant correlations that are significant within the <0.05 error level. Between Kolb LSI and Bartle (and vice versa) the only significant effect is reported for Kolb LSI *Thinking* and Bartle *Achiever* (0.277).

Considering the correlations of BFI-K dimensions and thus the predictability of dimension of the two other models based on BFI-K values as stated in the motivation of this publication two significant correlations can be observed. First, between BFI-K *Conscientiousness* and Bartle *Socializer* there is a positive correlation (0.276).Second BFI-K *Openness* correlates negatively with Kolb LSI *Experiencing* style (-0.287).

As displayed in table 2 the pupils proficiency level (scaled to the interval (0,1) as well) correlates significantly positively within the error probability of 0.05 with Bartle Explorer (0.249) and BFI-K *Conscientiousness* (0.413). The later even within significance level 0.01. A significantly negative correlation within the 0.05 error probability was found with Bartle Killer (-0.242) and BFI-K Extraversion (0.240). The pupils own agreement to the statement “To the most of my classmates I have a positive relationship” on a Likert scale from 0 to 3 (I totally disagree – I totally agree) is named as *climate* in the table 2 and correlates positively with Bartle Achiever (0.243) and with BFI-K Neuroticism (0.278) within the significance level 0.05. Like the proficiency level the climate correlates as well within the significance level of 0.01 negatively with BFI-K Extraversion.

Table 2: Correlations (Pearson) of pupils' level of proficiency (math) and positive social connectedness (climate) with the three models' dimensions (Bartle, Kolb LSI and BFI-K).
*** significance level 0.01 ** significance level 0.05**

	proficiency level (*N* = 70)		climate (*N* = 72)	
	corr.	*sig.*	*corr.*	*sig.*
Bartle (Achiever)	.016	.896	**.243***	.040
Bartle (Explorer)	**.249***	.037	-.029	.807
Bartle (Killer)	**-.242***	.043	-.042	.728
Bartle (Socializer)	.073	.550	-.140	.241
Kolb LSI (Experiencing)	.173	.152	-.134	.262
Kolb LSI (Reflecting)	.166	.171	.014	.906
Kolb LSI (Thinking)	.217	.071	-.116	.331
Kolb LSI (Doing)	.065	.590	-.026	.826
BFI-K (Extraversion)	**-.240***	.045	**-.331****	.005
BFI-K (Agreeableness)	.023	.850	-.008	.945
BFI-K (Conscientiousness)	**.413****	.000	-.050	.674
BFI-K (Neuroticism)	-.128	.292	**.278***	.018
BFI-K (Openness)	-.139	.251	.196	.098

5 Conclusions and implications for the design of games for learning

All in all, the results do not fulfill the expectations of the study. Predicting the playing style preferences based on the BFI-K profile of a gamer is only possible for the Socializer playing style. Moreover, the correlation of 0.276 does not even support a strong predictability based on the BFI-K *Conscientiousness* value. Still, it sounds like a reasonable effect that pupils with higher values in *Conscientiousness* are as well more likely to focus in computer games on *Socializing*. For the learning style preferences the situation appears to be similar. Most of the learning style preferences cannot be predicted based on the BFI-K values. Only for Kolb LSI *Experiencing* there is a significant effect that this value might be higher if a gamer has a low *Openness for experiences* (significant negative correlation of -.287). This is a surprising result as it might be a reasonable hypothesis that these two dimensions are potentially positive correlated. This could be corroborated by the not significant small positive correlation (0.137) to Bartle Explorer, but is at the same time contradicted by the negative correlation between Bartle *Explorer* and the Kolb LSI *Experiencing*. Thus it remains unclear why *Openness* for experiences and *Experiencing* correlate negatively.

Beside the fact that the main expectations could not be fulfilled, it is worth to discuss the strong significant correlations within the models. Usually the model’s dimensions tend to be independent from each other to allow a maximum of diversity within the combination of values for the model dimensions.

While the negative correlations of Bartle's playing style preferences can be explained by the nature of these styles and as argued by Bartle (1996) himself in his publication, it remains unclear why all learning style preferences correlate among each other and why there are significant correlations within the BFI-K dimensions. The latter are explicitly designed as independent dimensions and are evaluated in manifold studies. Thus it can be concluded that the sample group of pupils in the study at hand is not representative and has a bias concerning the personality dimensions of the pupils. This could be influenced by the schools we selected, the personality state most pupils at 9th grade are in or as well the mood in which they were while answering the questionnaire. Still, none of these effects seems to be really a probable cause of the correlation effects in the normally independent personality dimensions of the five Neo-FFI dimensions.

Mainly the strong dependency of the Kolb LSI style preferences appears to be the most surprising effect of the within-model correlations we found. Basically these values can be interpreted as such, that all pupils train and elaborate their skills within the four learning style dimensions in parallel and do not focus on one learning style. This can be interpreted as a direct result of a diversified teaching and instructional setup in the school classes and thus is a quality measure of the didactically well-designed education the pupils received (i.e. the more positive correlations within the Kolb LSI model the better the educational design). This is supported by the fact that Kolb and Kolb (2005) themselves describe it as one application scenario for the LSI to find the learning style with the most deficits for each individual with the aim to improve the competencies in this learning style with the long-term aim to have balanced values for all learning styles of each individual. This seems to be the case for the pupils in the study described here.

Concerning table 2 the primary interest lies on the predictability of the values for the models of Bartle and Kolb LSI. None of the analyzed items correlates significantly with any of the Kolb LSI dimensions; even though several more items (not listed in the table) from the electronic questionnaire where as well analyzed for correlations (like computer expertise level and amount of time per week using computers). As a result, the significant correlations with the Bartle playing styles *Achiever*, *Explorer* and *Killer* remain (Climate correlates significant positively with Bartle Achiever .243; proficiency level correlates significant positively with Bartle Explorer .249 and significantly negative with Bartle Killer -.242). Even though it might be expectable that a pupil with a positive climate (social relationship) to his classmates may have then as well the playing style preference of Bartle's *Socializer*, it can be argued that there is no significant correlation in this study results, because such pupils might be more focused on using the social interaction and connectivity for achieving personal goals (*Achiever*). Indeed not surprisingly there is a significant correlation among proficiency level and Bartle's *Explorer* playing style preference as it suits highly skilled pupils to be as well eager to know all approaches to a quest or task and to know the most efficient (and rarely known) way to approach problems. Pupils with a high proficiency level significantly tend to dislike the Bartle's *Killer* style of playing as they might not focus on causing negative impacts on their peers due to an already reached high level of competency (proficiency). As a consequence from the results displayed in table 2, predictions can be made based on the *climate* values and proficiency level of a pupil. The higher the two values, the more she may as well prefer the Bartle player styles *Achiever* and *Explorer* and won't tend to the *Killer* style.

In summary, the study revealed that the prediction of Bartle playing style preferences or Kolb LSI learning style preferences is not sophisticated possible on basis of the NEO-FFI personality values conducted from the BFI-K questionnaire. Precisely at least based on the data of the study described here such conclusions cannot be made. Still, the results showed some significant and positive correlations to predict Bartle's playing style preference for *Socializer* based on BFI-K *Conscientiousness* and Kolb's LSI *Experiencing* based on the BFI-K *Openness* value*.* Still, for the three other playing style preferences of Bartle's model (Achiever, Explorer and Killer) a tendency can be seen that they are predictable based on pupils' proficiency level and perceived social connectivity to their peers.

A conclusion for the design of games and game-based learning applications is the validity to model the dimensions for learning style preferences and player style preferences still separately within the game engines as there is no common strong correlation with the personality model of NEO-FFI. The described study revealed some (small) significant correlations that primarily allow drawing some predictions for Bartle's playing styles of a person when using additional item values. Researchers are encouraged to further investigate how the established models can be combined and used most effectively together to keep players in the state of flow in both models' worlds: playing and learning.

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