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Review

Video game personalisation techniques: A comprehensive survey ☆

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ABSTRACT

Personalisation is the automatic customisation of content and services based on a prediction of what the user wants. Common examples of personalisation can be found in websites that automatically recommend news items or products based on the similar behaviour of other users. In the video game domain, personalisation involves constructing a system capable of tailoring video game rules and content to suit some aspect of the player, e.g., a player's gameplay preferences, playing style, or skill level. The result of personalisation is a video game that can adapt to suit individual players while they play in order to more effectively entertain, learn, or communicate. In this paper, we survey the most relevant trends and directions of research in personalisation for computer games, a true multi-disciplinary problem requiring contributions from areas as diverse as artificial and computational intelligence, game studies, psychology, game design, and human–computer interaction.

Contents

1. Introduction and overview

Personalisation is the customisation of content and services based on a *prediction* of what the user wants. Common examples of personalisation can be found in websites that recommend news items or products based on the past behaviour of the user or the similar behaviour of other users. We are primarily interested in *automated* personalisation, in which such customisation is performed automatically by/within an application, and this review focuses on reviewing work on this capability within video games.

In the video game domain, personalisation involves constructing a system capable of tailoring video game rules and content to suit some aspect of the player (e.g., a player's gameplay preferences, playing style, skill level, etc). The result of personalisation is a video game that can *adapt* to suit individual players *while* they play in order to more effectively entertain, learn, or communicate.

A system that dynamically modifies or generates video game content and rules could theoretically also do so by basing its decisions on some kind of input *other* than the player, e.g., as done by "context-based" games. For example, a system that adapts the attitudes of non-playable characters in a role-playing game can do so

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Table 1
Examples of how video game personalisation has been applied, categorised by both the type of player data used (i.e., input), and the gameplay being personalised (i.e., output).

Preferences	Role-playing game maps [5] Difficulty, weapon control, and objectives [6] Platforming levels [7]
Personality	No current games applications
Experience	Camera position [8,9] Plot/story points [10] Platforming levels [11,12] Action game levels [13]
Performance	Platforming levels [14] Enemy type and count [15] Platforming levels and dungeon structure [16] Battle missions [17,18]
In-game behaviour	Quest structure [19,20] Weapon behaviour [21]

in a randomised fashion, or in a way that is dependent on the time of day. In spite of this, much work describing an adaptive video game system still places exclusive focus on a single input source: the player [1–3]. This exclusive focus is hardly surprising given the core purpose of a video game: to entertain, communicate with, and educate a population of human players that each have a varying assortment of tastes and attitudes.

However, while the potential of video game personalisation is significant and can enhance a video game's effectiveness and in some way account for variety within a population of players, achieving personalisation to any meaningful degree is a challenge. Even a more widely accepted application such as "dynamic difficulty adjustment" [4], defined as the adaptation of a video game's difficulty to match the player's skill level, is still far from becoming a staple feature of modern video games. Again, this is hardly surprising when you consider the profundity of what video game personalisation is really setting out to achieve: the construction of models that describe human characteristics and, in many cases, the reliable interpretation of in-game player behaviour.

In this paper, we survey work relating to video game personalisation in sections that correspond to five ways that players are often said to differ from each other:

1. By preferences (i.e., gameplay that players find appealing).
2. By personality (i.e., distinctive character of players).
3. By experience (i.e., how players emotionally and cognitively respond while playing).
4. By performance (i.e., the degree and rate of player achievement/progression).
5. By in-game behaviour (i.e., the actions a player made within the game).

Each section introduces each player differentiation category before describing examples of their application to video game personalisation. Table 1 contains all references for each category's applications for quick reference. Our discussion of other work in this paper aims to identify key research avenues that require further exploration.

Other surveys related to the topic of video game personalisation include [22,23] which both survey the broad field of player modelling with a focus on a better understanding of how players behave in games.

2. Player preferences

In this section we review and compare work that focuses on differentiating players by how much they do or do not like particular types of video games (e.g., puzzle games, racing games), or elements of video game design (e.g., "competition", "discovery", and "strategy"). This is often described as a *player's preferences.* Though this section focuses on preferences and how they have been applied to personalisation, we also briefly discuss work on player motivation and list types of gameplay that others have identified. We introduce motivations and gameplay types in this section because they can also provide insight into different preferences that a player might have. In fact, we draw upon work in all three categories (i.e., preferences, motivations, and gameplay types) to form a comprehensive list of preferences.

2.1. Our view of player preference

We start our discussion of preferences by first establishing how our view of preferences differs from other work. This is important because the term "player preference" has been used ambiguously in the literature on this topic.

Firstly, we view a player's preferences as being equivalent to a player's "taste" in video games that is potentially *independent* of commonly held video game genres such as the real-time strategy (RTS) or role-playing game (RPG). For example, a player can have a preference for gameplay concepts such as "strategic planning" or "player cooperation" that can be fulfilled in different measures and forms by multiple genres. For example, strategic planning is often found in RTS's where the future production and location of buildings and units require planning, and in RPG's where the future development and specialisation of the player's character requires forethought. Similarly, player cooperation is often found in both multi-player RTS's and multi-player RPG's. This view is in contrast to another that instead equates a player's preferences to being an abstraction of a person's "play style" *within* a particular video game genre. For example, a player can have a preference for gameplay activities such as "exploring/adventuring" or "collecting" within the role-playing game genre [24,5].

Secondly, we view a player's preferences as having a similar structure to psychological models of personality that are "trait-based" such as the Five-Factor Model [25] rather than "type-based" such as the Myers–Briggs Type Indicator [26]. Our use of these terms throughout refers to their respective structures and separate that from the psychological reasoning behind them.

2.2. Type-based and trait-based preferences

An early example of a type-based player preference model is Bartle's taxonomy [24] that views online role-playing game players as either "achievers", "explorers", "socialisers", or "killers". This has since been extended to eight types rather than four [27]. Other examples have since followed a similar approach, but none present a model that can be confidently applied to video game personalisation for various reasons. For example, [28] does not include details of the instrument used in *Wizards of the Coast*'s market research, [29] is based only on informal observations of player behaviour, and while [30] is based on empirical evidence it is self-admittedly "very sketchy and incomplete". All of these examples are not only what we consider to be the *play style* view of preferences but are also *type-based* without exception. [31] is an example that deviates from this trend and describes a set of preferences where each item corresponds to a common video game genre or subgenre from the set of nine categories described at length in [32]. This is an example of yet another player preference perspective, one defined by viewing each preference as being equivalent to a game genre. [33] details at length the arguments for both type-based and trait-based models, but states that, for the same reasons that psychological models have moved from being type-based to trait-based, future studies should focus on investigating a trait-based player model structure. Bateman et al. [33] also points out that without empirical evidence the four types in Bartle's model may or may not be mutually exclusive (i.e., it is possible a single player possesses attributes described by two or more types). Indeed, a weakness in type-based models might be that they group together multiple attributes, ruling out the possibility that players can be described by a set of attributes that occur in different types.

Despite a general lack of evidence for the assumptions that both type-based and trait-based preferences models hold, *genre-specific* models continue to be applied to video game personalisation. For example, "GameForge" is a project that currently personalises maps [5] and plot points [34] in a role-playing game to preferences expressed either via survey or previous in-game behaviour. This project has not yet reached the final implementation stage with an evaluable player model. Dias and Martinho [6] elected to apply the preference model developed by [30] to personalise elements of an action-shooting game. Despite performing a preliminary evaluation of their methodology, they acknowledge that further development and evaluation is required before they can show whether their personalisation has a positive effect on the player's experience. Finally, [7] uses both survey questions and in-game behaviour in the same experiment to elicit player preferences and then personalise a platform game. However, evaluation was again lacking in that it was performed using only four players, and like [28], does not include a complete description of the survey used. Unfortunately there was also no mention of whether the survey and in-game behaviour features they used correlated.

In summary, both preference-driven personalisation applications and the preference models they are based on require further evaluation before their effectiveness in affecting player experience and capacity for describing players meaningfully can be shown. Ultimately, we postulate that comparing the techniques and models used in this area is better left to when this proper evaluation has occurred. Additionally, further work in the area is required before any hypothesis of a trait-based preference model being more descriptive and effective than type-based models can be confirmed or otherwise rejected.

2.3. Player motivations

In this subsection, we describe work that focuses on player motivations rather than preferences [35]. Unlike preferences, which generally equate to what players like or prefer, motivations relate to the explanations for why people play video games. There is some overlap: for example, a player could have a preference for a gameplay element such as social interaction and also be motivated to play by the same aspect. However, the relationships of preferences and motivations to gameplay are distinct. Further, not all motivating factors make sense as a preference. For example, a player could be said to be motivated to play by the desire to "escape" from the stress and problems of the real world [36] but it may not be appropriate to infer that the player has a preference for escapism.

We have identified six key pieces of work that describe lists of player motivations found through their investigation into why people play particular types of video games. Malone [37] describes four intrinsically motivating game playing factors in games and found that players are motivated by these factors to varying degrees. Yee [38] quantitatively identifies ten motivational factors that drive the play of massively multiplayer online role-playing games (MMORPG's). Based on the results of a 40-question survey, Yee's motivational factors offer some explanation for why players choose to play these games for different reasons, and for how different players are affected by MMORPG gameplay. Schultheiss [39] surveys a group of 150 massively multiplayer online (MMO) players to assess how significant different *usage motivation* and *gameplay experience* factors are in keeping players "tied to a game". The primary finding here was that, while each motivation affected players differently, some motivation and experience factors were generally more significant influencers of behaviour than others. Based on the work of [38], Tychsen et al. [40] develops a motivation survey applicable to both single-player and multi-player role-playing games (RPG's) to form ten motivational factors. They found that, like [39], different motivational factors were generally ranked higher than others and also notes their findings suggest different players vary in how narrow or broad their motivations for playing are, and that a complex relationship exists between some motivational factors. Bostan [41] adapts Murray's Psychogenic Needs [42] to the RPG domain, forms a taxonomy of 27 player motivations, and argues that such a taxonomy can be useful in formulating a motivation framework that is applicable across multiple video game genres. Finally, Kallio et al. [43] conducts a cultural study and identifies a list of "player mentality profiles" that describe nine reasons for playing video games, finding that a majority of play occurs between only two of them (relaxation and entertainment). Interestingly, player motivations have not, to the best of our knowledge, yet been applied to video game personalisation in any context.

2.4. Gameplay types

Finally, we list selected pieces of work that describe either their own list of gameplay types, or their own list of explanations for why video games are fun. Work in this category is often used to inform the object of a player's preferences; for this reason, we briefly describe them in this section.

Callois [44] describes a set of characteristics of non-digital play that can be used to divide games into four discrete categories according to whichever characteristic is particularly dominant. The chosen characteristics can each be summarised as *competition*, *chance*, *simulation*, and *vertigo*. An example of other work that seeks to confirm the appeal of these categories (as well as that of [24] and others) is [45], which explores how a modern understanding of the human brain's neurobiology can be applied to explain why certain elements of games are inherently appealing to players.

Lazzaro [46] investigates the related question of *why* people play games and presents four "keys" to eliciting a set of emotions in players without the use of a story. The emotion set was identified during observation of 45 participants while they played a variety of video games and is noteworthy for its data-driven approach.

Hunicke [47] also tries to better understand the appeal of games by formulating a list of eight video game *aesthetics* which they define as "desirable emotions evoked in the player" during play. They go one step further and use these aesthetics to describe the player-game interaction process with greater precision than generic descriptors such as "fun" and "gameplay".

Rollings and Adams [32] add to the discussion by describing ten video game genres, each defined by popular mechanics and tropes that aim to elicit a particular kind of gameplay experience. [48] iterates on these genres while also including a more specific set of gameplay challenge types.

Sweetster and Wyeth [49] outline a "GameFlow" model for evaluating a player's enjoyment with a video game by adapting the concept of *flow* [50] to games. Included with their model is a list of criteria aimed to help designers test the enjoyability of their games. Lastly, and also intended to assist designers with the formulation of successfully appealing video games, [51] presents a list of 100 questions commonly faced by game developers. A subset of these, including those labelled as "skill vs. chance" and "competition" as examples, can themselves be used as the basis of a smaller list of ways that video games are known to often appeal to different players.

3. Player personality

Personality, a psychological construct said to partially explain human behaviour, is yet another way of describing differences between players. Examples of common personality models are the Myers–Briggs Type Indicator [26] and the Five-Factor Model [25]. Personality-based techniques are related to type-based preference-based approaches, leverage existing general personality-classification frameworks, as opposed to constructed game-specific profiles. [33] discusses the potential disadvantage of applying constructs such as this to the video game domain and favours an approach that specifically applies to video game players. However, in spite of this, there have been successful applications of personality models to this domain. For example, Zammitto [31] shows how a player's preference for eight out of twelve game genres partially correlate to the Five-Factor Model. Additionally, there are other examples of the correlation between player behaviour and personality survey data. [52], while inconclusive in its findings, uses descriptive statistics to show similarities in how participants answered both a Five-Factor Model survey and a player habits survey. [53] compares responses to the Five-Factor Model with the chat logs players produced within the *Second Life* virtual world. The comparison was achieved using linguistic measures on the chat log data and a statistically significant correlation was found using an analysis of variance (ANOVA test). The most relevant finding seemed to strongly correlate conscientiousness with locomotion and geography features. More generally, most correlations in the paper seemed to be questioning several patterns outlined in previous related work. [54] also found a statistically significant correlation, this time between in-game behaviour data from the computer role-playing game *Neverwinter Nights* and all traits described by the Five-Factor Model. While it is unclear what correlation mechanism they employed, they mention that they evaluated its statistical significance using Cohen's effect size interpretation method [55]. Finally, in a similar experiment, [56] also reports significant correlation between in-game behaviour and the Five-Factor Model using another computer role-playing game: *Fallout 3*. Despite reporting statistically significant results, [56] also do not list the correlation measure used and acknowledge that their strength of correlation "seldomly reached an effect size larger than 0.5" and that, in future, they should gather data from a larger number of participants than the current total of 36.

We close this section by remarking that the benefits of observing personality through in-game behaviour have not yet been exploited in video game personalisation, nor is there any inclusion of that as future work, at least to the best of our knowledge. The general intention behind work in this area is to instead better understand the relationship, if any exists, between gameplay and personality.

4. Player experience

The rationale underlying *experience-based* video game personalisation is that players who vary in their preference toward particular videogame types or variants can be described by *how* they experience (i.e., respond) to them. [57] surveys the specific area of *experience-driven procedural content generation (EDPCG)* and provides a thorough summary of what is actually meant by "experience" in the context of video game personalisation: "the synthesis of affective patterns elicited and cognitive processes generated during gameplay". Personalising a video game based on how players are currently experiencing, or are predicted to experience, gameplay circumvents the need to understand characteristics about the player and how they relate to facets of gameplay by concerning itself only with optimising the player's experience. For example, two-dimensional platforming game levels have been automatically designed and generated in this vein, to optimise predictions of a player's experience of engagement, frustration, and challenge [12].

Observing the experience of a user (in this case, player) is often done using either one or a combination of two methods: objectively via physiological signals, or subjectively via self-report. Physiological signals (e.g., heart rate, skin conductance level, EEG) offer a continuous stream of data that is by and large unable to be manipulated by the subject (i.e., player) and is instead produced involuntarily. For this reason, they are considered to be free from the same contaminating factors known to reduce the reliability of self-reported data. [58] lists these factors as "participant answering style, social desirability, interpretation of questionnaire item wording, limits of participant memory, and observer bias". However, physiological data often requires complex equipment and is time-consuming to coordinate with every participant required to attend an experiment in-person and tested either one at a time or in very small groups depending on equipment and coordinator availability. Secondly, and more importantly than the logistic complexities, physiological data alone provides no meaningful explanations for itself and thus requires observation methods and correlation with other data sources in order to interpret its meaning. This includes a more direct data source: self-reported data. Experimental designs incorporating self-reported experience data or applying it to personalisation include the use of open-ended questions [10], post-game commentaries [59], and two or four-alternative forced choice method [60,11,61]. Given that neither physiological and self-reported data is ideal, a combined *psychophysiological* approach has also been taken to player experience research. This includes the successful correlation of both types of data [62,63] and the application to video game camera personalisation [8].

As with player preference and personality, the inference of player experience with a personalisation variant from a player's in-game behaviour has also been attempted so that players do not need to self-report their experience after each game. A notable example of this is [11], which shows that using a two-dimensional platform game that limits the player to only running, jumping, and using an in-game item is enough to successfully predict six affective states observed via self-reported data at an accuracy that ranged between 73% and 91%. We view this as added evidence that a player's in-game behaviour can be used to predict a characteristic of the player, even in simple games with a limited range of player expression.

The work in [13] instead presents procedural generation of content (e.g., enemies, power-up items, etc.) in an action *Alienbreed* style of game. User ratings are fed to a Naive–Bayes classifier that predicts which content players are more likely to be willing to experience in their future play. Such a player model drives the evolution of new game levels that are more akin, in fact, to what players want. Such data was more recently correlated to self-reporting data, and showed with high levels of significance ($p < 0.01$) that players' experience could be vastly improved when compared to a random generation experience (as seen in most *rogue*-style games).

For the sake of completeness, we introduce another example that incorporates both in-game behaviour and a player's self-reported preference of particular game variants to develop what was dubbed a "player model-driven preference learning" approach tested in a personalising maze-arcade game [9]. They report a small but statistically significant improvement in the prediction of a player's experience using both types of data; this serves as evidence for how multiple types of player data can be used to provide a more complete model of a player.

Finally, we compare experience-driven personalisation to other types surveyed in this paper (e.g., preference or personality profiledriven) in greater detail. We have already pointed out that defining players by how they experience a video game removes the need to understand anything else about the player or what they are playing, but experience-driven personalisation also has the added advantage of skipping another step: evaluating whether the personalisation is having the intended effect on the player. This can of course be skipped because knowing the effect of personalisation is required to achieve experience-driven personalisation in the first place. However, with the added simplicity comes limitations. Experience-driven personalisation can only ever personalise according to facts of experience.

The scope for personalisation beyond this includes personalising video game elements to other characteristics of a player, which may include demographic, preferences, or attitudes. Also, the experience-driven approach is not suited to cases where the designer desires control over how the personalisation system should behave with respect to known differences between players. Experience-driven personalisation only permits designers to alter facets of experience, whether that be optimising for the player or according to their own intent. Permitting designers to determine how a personalisation system should behave in accordance to some other facet of the player apart from experience is the main advantage, at least in theory, of profile-based approaches.

A final limitation lies in the difficulty of gathering enough data to know how players experience every variant produced by a personalisation system (e.g., every kind of level or other game content type that is dynamically generated). In order to personalise according to experience, the system needs to know how any particular personalisation variant is likely to be experienced. It is not hard to imagine that some procedural-content generation systems, containing several input variables that can each have several values, might require a data set containing thousands of player experience observations. This problem would only increase for personalisation systems that are managed by the behaviour of an AI agent, whose rules determine a potentially vast number of personalised game variants. This final limitation of experience-driven personalisation could be mitigated by a player experience model constructed from player behaviour, as per the case in the aforementioned example of [11]. In other words, this concern would cease to apply if both (a) the player experience model proved to be reliable for a sample of test cases deemed representative of the personalisation full set of variants, and (b) the personalisation system did not significantly modify the relationship between player experience and in-game behaviour assumed by the model.

5. Player performance

In this section we review work that focuses on describing players by the degree of ease or difficulty by which they overcome obstacles found in different games—i.e., matching a particular game's difficulty to the player's current skill level. Applying this method of player differentiation to video game personalisation is often called *Dynamic Difficulty Adjustment (DDA)* [64] and aims to keep the game's difficulty at a level balanced between boredom and frustration as dictated by the theory of Flow [50]. Successfully achieving DDA is non-trivial, however, since players are said to develop their game playing skills at different rates. Jennings et al. [14] acknowledge this and attempt to address it with a DDA system that dynamically generates levels in a two-dimensional platform game according to a player's changing skill level, obtained by continuously monitoring the player's current level of in-game performance. Zook and Reidl [18] agree with this approach and observe that a player's performance from in-game behaviour is objective, whereas the player's perceived difficulty is subjective. For this reason, Zook and Reidl view the adaptation of difficulty based on observed performance as more reliable than that based on self-reports of difficulty. However, Jennings et al. [14] make no mention of taking a player's preference for ''difficult experience'' or ''challenge'' into account when dynamically adapting their platform game's difficulty. Though neither [16] nor [17] incorporate a player's preference for challenge into their DDA systems, they both list this an avenue of further research. We agree with this hypothesis that players do possess such a preference for challenge, especially following a recent study on the effect of game difficulty on different players [65] that confirms players have a varying desire to challenge themselves.

A unique example of personalisation is [15]. This work combines a player's in-game behaviour with data obtained from a brief pre-game preference survey to adapt the difficulty of enemies in a top-down shooting game according to the predicted frustration and boredom levels of players. The uniqueness of this example lies partially in the combination of preference data with in-game behaviour; however, the two types of data are not correlated—this would be a valuable extension. The authors note that their preference survey consists of two items: ''what is the preferred level of difficulty'' and ''what is the preferred weapon type''. [15] is also unique when compared to the other personalisation examples in this category by also incorporating elements of player experience—i.e., boredom and frustration—thus giving it the added benefit also afforded to other personalisation examples described in Section 2. However, apart from this particular example, other DDA examples currently lack any evaluation of whether they achieve their intended effect on player experience. We note that this lack of evaluation, one that also exists with the preference-based personalisation examples in Section 2, points to a general immaturity amongst current applications of video game personalisation.

6. In-game player behaviour

This section compares work that considers a player's in-game behaviour *alone* as suitable input to a video game personalisation system. The work described in previous sections views in-game behaviour as meaningful input to a personalisation system but the key distinction is that work in this category does not infer the behavioural data's meaning from other data (e.g., preferences, personality, etc). Work in this category instead infers meaningful facts about the player (e.g., their general playing style) from the behaviour data itself.

As one example, Drachen et al. [66] categorised players who were particularly adept at solving in-game puzzles in an action-adventure game into the category of ''solvers'', without additional correlation to other psychometric or physiological data. Other examples, using different video game genres and analysis techniques, are otherwise similar in nature by way of also classifying players into various groups based on their playing style. Matsumoto and Thawonmas [67] classify massively multiplayer online role-playing game (MMORPG) players using Hidden Markov Models (HMM). Tan and Cheng instead present the IMPLANT [68] architecture, which extracts both a POMDP (Partially Observable Markov Decision Process) modelling a player in a tennis game and a fully-observable MDP (Markov Decision Process) of the underlying game environment. Abstract policies are then pre-computed from each model and merged into a single optimal policy that allows to synthesise an artificial companion for a game of doubles in the aforementioned tennis game. Tychsen and Canossa [69] attribute ''persona'' types to players of an action-stealth game. Anagnostou and Maragoudakis [70] cluster players of an action-arcade game using the Clustering Using REpresentatives (CURE) algorithm. Ramirez-Cano et al. [71] cluster players of an action-hunting game using a three-level ''meta-clustering'' form of analysis. Gower et al. [72] describe players of two different action games using multi-class Linear Discriminant Analysis (LDA).

Despite using a variety of different methods, the similarities between the above examples are clear. The exception is [72], which reduces the dimensionality of in-game behaviour data to produce a trait-like description of players, rather than assigning each player to a set of distinct player types. For reasons discussed in Section 2, we view a type-based description of players to be an oversimplification that, if evaluated, is likely to have only a limited effect on the player's experience when applied to personalisation. While trait-based models introduce complexity into personalisation systems that are already highly complex in nature, we expect the increased detail afforded by trait-based player descriptions to be a worthwhile tradeoff.

Additionally, there are examples of work in this category being applied to personalise both the quest structure in a role-playing game [19,20] and particle system behaviour of weapons in a space-action game [21]. Unfortunately, the personalisation techniques in both of these projects are yet to be formally evaluated by testing their effects, either quantitatively or qualitatively, on the experience of players.

Methodologies exemplified by this category of work, though having the benefit of being straightforward, are limited in their use because they rely upon in-game behaviour data alone. Bakkes et al. [73] survey work according to how player behaviour is modelled—e.g., modelling player actions, tactics, or strategies—and discuss how the inferral of a psychologically or sociologically verified profile from player behaviour can *extend the applicability* of player behavioural modelling, noting types of video game personalisation as examples. We believe this limited applicability also applies to the examples above that classify players according to their playing style. Without correlation with other types of data, in-game behaviour alone can only produce objective facts about what is happening in the game: e.g., how successful the player has been in the past, or the probability that a player will engage in particular game activities in the future. Personalisation based on these objective facts may, once properly evaluated, prove to be effective tools for limited types of video game personalisation. However, on their own they are not enough to confidently answer questions that are more subjective in nature: e.g., why does the player prefer to engage in a specific game activity, or how will the player experience an adapted piece of game content. If designers in charge of controlling the behaviour of a personalisation system were able to confidently answer these "deeper" questions, then they would be able to better understand the impact of their personalisation design choices prior to the evaluation of their effect, as well as possibly learn more about the game they are creating. For example, consider two possible reasons for why some players actively skip fighting/combat sections in a hypothetical game more than others: they dislike having to repeat a sequence if they lose when they could have been progressing through the game's story, or they find that this game's particular combat design is overly chaotic and dependent on chance. If the designer of this game is presented with statistics derived from in-game behaviour data, they can only safely conclude that some players dislike the game's battle system. The designer could address this using personalisation so that the number of battles required to progress are reduced for these players. However, while the problem appears to be solved, the underlying issue remains unknown to the designer. The same reason that some players had for disliking the combat system could also apply to other game activities, and another less-than-optimal personalisation strategy may be enacted to identify that as well. An experienced designer could intuitively identify the underlying problem without supporting player data/observations, but perhaps not.

In addition to being able to help explain the *cause* of in-game behaviour, reliably correlating behaviour with other forms of data also greatly *simplifies* the observation process that ordinarily requires additional psychological or physiological instruments. While this would be of great benefit to the research community, the most significant effect would likely be felt in the games industry.

Currently, using existing video game hardware and services already available to consumers, a commercial video game has only the player's input (i.e., their in-game behaviour) to use as the basis for personalisation. This input currently varies from traditional keyboards, pointers, and controllers to the more recent motion-tracking devices that are available on current-generation home consoles. If a video game developer wanted to enable personalisation based on an alternative source of input, they would have to develop and market alternative hardware themselves. The promise of alternative physiological input devices such as Nintendo's *vitality sensor* and Ubisoft's *Ozen* exist, but both projects have been long-delayed after being first announced in 2010.[1] Regardless, in light of that and other more recent suggestions from other developers that they will develop controllers that observe players biometrically,[2] traditional player input is likely to remain the only source of player data ready for use in the near future. On the psychological front, there is the rare example of personalisation in the commercial video game *Silent Hill: Shattered Memories*, a psychological-horror game that personalises in-game models and elements based on a psychological test conducted by a non-playable psychologist character. While this explicit, self-reporting process is credible in this case, the approach requires a suitable narrative context to avoid becoming disruptive or burdensome. A context such as this can rarely exist naturally without feeling contrived, and the novelty of having to complete a mandatory survey at the beginning of a video game in order to obtain access to a personalised version would quickly wear off. For these reasons, we consider it of high importance to continue investigating the correlation of player's in-game behaviour to other data ordinarily requiring the psychological and/or physiological instruments described above.

7. Conclusions

Throughout this survey, we have specifically focused on four important requirements for the development of a commercially applicable means of video game personalisation:

1. Selection of a meaningful player characteristic to drive personalisation.
2. Observation of the player characteristic that is reliable and practical.
3. Integration of the observation method into a game adaptation system.
4. Evaluation that verifies the personalisation has the intended effect on player experience.

We have defined a specific view of *player preference*. We have noted a general lack of requirement 4 above in every category of existing personalisation applications, except for (to some degree) those described in Section 4, where the evaluation is implicitly achieved by the method itself. Moreover, we have argued that correlating in-game behaviour data with other forms of data, as has shown promise in the case of both player personality and experience data, has a positive two-way effect on both types of data. Specifically, as more is known about why the in-game behaviour occurs, the more *widely applicable* it becomes to

[1] Ozen has an official 2014 release date, but it has not been released yet at the time of this writing.

[2] For more information, read the full interview here: http://www.theverge.com/2013/1/8/3852144/gabe-newell-interview-steam-box-future-of-gaming.

personalisation. Moreover, if psychological or physiological data can be inferred from in-game behaviour then the *practicality* of their application to personalisation greatly increases, potentially to the point of commercial adoption.

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