Review of Intrinsic Motivation in Simulation-based Game Testing

Shaghayegh Roohi[1], **Jari Takatalo**[1], **Christian Guckelsberger**[2], **and Perttu Hämäläinen**[1]
[1]Aalto University, Finland, Email: {shaghayegh.roohi, jari.takatalo, perttu.hamalainen}@aalto.fi
[2]Computational Creativity Group, Goldsmiths, University of London, London, UK, Email: c.guckelsberger@gold.ac.uk

This paper presents a review of intrinsic motivation in player modeling, with a focus on simulation-based game testing. Modern AI agents can learn to win many games; from a game testing perspective, a remaining research problem is how to model the aspects of human player behavior not explained by purely rational and goal-driven decision making. A major piece of this puzzle is constituted by intrinsic motivations, i.e., psychological needs that drive behavior without extrinsic reinforcement such as game score. We first review the common intrinsic motivations discussed in player psychology research and artificial intelligence, and then proceed to systematically review how the various motivations have been implemented in simulated player agents. Our work reveals that although motivations such as competence and curiosity have been studied in AI, work on utilizing them in simulation-based game testing is sparse, and other motivations such as social relatedness, immersion, and domination appear particularly underexplored.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords
Player Modeling; Game Testing; Intrinsic Motivation; Artificial Intelligence; Emotion;

INTRODUCTION
Game design is typically an iterative process of implementing a prototype or game feature, testing it with players, and improving the design based on test feedback. The testing and improvement iteration is necessitated by the difficulty of predicting game and player behavior and the player experience arising from play. The emerging field of simulation-based game testing holds the promise of providing faster and more cost-effective feedback to game designers by replacing human players with simulated agents. Ultimately, if provided with fully human-like simulated players, one could automatically optimize designs by allowing an algorithm to carry out parts of the design and testing iteration *in silico*.

Following the recent advances in deep reinforcement learning (e.g., [57, 84]), AI players can already learn to win many games, and different degrees of skill can also be simulated [97, 46]; a remaining research problem is to model the aspects of human player behavior not explained by purely rational maximization of in-game rewards, i.e., cognitive biases, emotions, and intrinsic motivations. The latter refer to psychological needs that elicit motivation even in the absence of extrinsic motivation and rewards such as game score, and constitute a major piece of the puzzle.

In this paper, we provide the first systematic review of intrinsic motivations in player modeling and simulation-based game testing, in an attempt to better bridge the growing, but so far largely disjoint fields of player psychology and game AI. We hope our work provides new ideas, goals and insights for AI researchers, and points psychologists and human-computer interaction researchers to new technological tools and computational models. Our work reveals that although motivations such as competence and curiosity have been studied in AI, work on simulation-based game testing is sparse, and other motivations such as social relatedness and immersion appear particularly underexplored despite the ample psychological literature on them.

In the following, we first explain the review methodology. To provide a clear structure for the rest of the paper, we have summarized the results in Table 2 at the end of the paper. We have divided the paper into three major sections, each corresponding to a column of the table. We first overview the major intrinsic motivations and psychological needs discussed in literature on motivation and games (Table 2 left). Subsequently, the motivations are used as lenses for analyzing AI research. We briefly review how the motivations have been implemented and utilized in artificial agents (Table 2 middle), and then systematically review the more specific domain of player modeling and simulated game-playing agents (Table 2 right). Each of the three sections ends with a brief summary, with overall summary and conclusions provided at the end of the paper.

METHODOLOGY
Since we aimed to both review the state of the art and identify underresearched areas in player modeling and simulation-based game testing, we adopted a process of 1) reviewing common intrinsic motivations discussed in player psychology and AI research, and 2) conducting literature searches specific to player modeling and simulation-based game testing, using both the generic term "intrinsic motivation" and specific motivation keywords identified in stage 1. Naturally, we also checked the related work cited by the found papers. We used Google Scholar as the primary search engine, as it indexes

CHI 2018, April 21–26, 2018, Montreal, QC, Canada
© 2018 ACM. ISBN 978-1-4503-5620-6/18/04. . . $15.00
DOI: https://doi.org/10.1145/3173574.3173921

multiple databases including both games, human-computer interaction, and AI publications. Table 1 details the literature searches conducted in stage 2, and Table 2 summarizes the results.

In stage 1, literature searches such as "intrinsic motivation" AND "computer game", or "intrinsic motivation" AND "artificial intelligence" returned thousands of papers, which we did not have the resources to go through systematically. Thus, we primarily relied on existing reviews and books [28, 36, 4, 7, 58, 21], augmented by going through the first 100 search results to sanity-check for major omissions. Our goal is not to contribute yet another comprehensive review of the broader field of intrinsically motivated AI, but instead focus on player modeling and simulation-based game testing. As summarized in Table 1, our more specific searches on player modeling and game testing returned a manageable number of papers.

A note on scope

Player modeling denotes the field of research focusing on computational models of players in games [93]. This includes multiple approaches such as gathering a dataset of human playtraces and training a machine learning model to predict the player's actions in a given situation. Our focus here is on algorithmic player modeling, i.e., approaches that explicitly implement behavioral laws and do not need extensive datasets, except possibly for parameter tuning. Such approaches offer greater flexibility of deployment, especially regarding automated testing and balancing of new games or game features for which data from human players is not yet available [24]. For a broader review of player modeling and the use of AI techniques in player modeling, we refer the reader to the work of Yannakakis and Togelius [93, 94, 95].

Our literature searches on player modeling also returned several psychological papers on, e.g., predicting motivation based on personality traits, other psychological variables such as self-esteem, or physiological signals [10, 9, 40]. These are likewise beyond the scope of this paper.

In summary, the excluded papers 1) did not propose or test any computational motivation model that can be implemented in a game-playing agent, or 2) used data-driven models that cannot necessarily be reapplied when game parameters change without collecting new data from human players [24]. On the other hand, we included papers that focus on non-player characters (NPCs) instead of simulated players; if such NPCs can generate plausible human-like behavior, the underlying techniques should be relevant for player modeling as well.

Table 1. Literature searches conducted and findings

Searched terms	Found papers	Included papers
"player modeling" and "intrinsic motivation"	69	[11]
"player modeling" and "competence"	132	[51, 55, 11]
"player modeling" and "autonomy"	147	[11]
"player modeling" and "relatedness"	23	[11]
"player modeling" and "curiosity"	136	[27, 11, 53, 65, 25]
"artificial intelligence" and "game testing" and "intrinsic motivation"	37	[20]
"artificial intelligence" and "game testing" and "competence"	76	[20]
"artificial intelligence" and "game testing" and "autonomy"	41	[20]
"artificial intelligence" and "game testing" and "relatedness"	10	0
"artificial intelligence" and "game testing" and "curiosity"	78	[20]
"player experience" and "intrinsic motivation" and "computational model"	32	[24, 50]
"player experience" and "competence" and "computational model"	53	[14, 3, 51, 55, 24, 50]
"player experience" and "autonomy" and "computational model"	48	[24]
"player experience" and "relatedness" and "computational model"	11	[23, 24]
"player experience" and "curiosity" and "computational model"	51	[24, 53, 50]

SIMULATION-BASED GAME TESTING

Before moving on to intrinsic motivation and its computational models, we first give a brief overview of the state-of-the-art in simulation-based game testing.

AI agents can learn to play many games as well as human players [57, 84]. AI agents can also model different levels of skill, e.g., by using Monte Carlo Tree Search (MCTS) with limited computing budget [97, 46]. Researchers have also emulated human-like imprecision, limited reaction time, and choosing incorrect actions [35, 39, 26]. Taken together, these results mean that AI agents can be used to answer many of the same questions as testing with real players, e.g., whether a level can be completed, what behavior emerges with different playing skill levels, or whether some weapon overrules others. However, quantifying the player experience beyond challenge and skill requires modeling of motivation and emotion.

In addition to the explicit, algorithmic motivation models reviewed in this paper, simulated player agents can also utilize implicit, data-based models learned from real players. For example, the state-dependent probabilities of actions observed in real players have been included in the upper confidence bound (UCB) formula of Monte Carlo tree search [17, 38]. Supervised imitation learning [63, 16], NeuroEvolution [67], and inverse reinforcement learning [44] are other methods which use human player data to emulate human game play.

As discussed in the next section, various player typologies represent categorizations of the space of motivations. The typologies have also been directly utilized in creating simulated player personas, each with their own (game-specific) objective or reward functions and preferred goals [31, 32, 30].

INTRINSIC MOTIVATION IN GAMES AND PSYCHOLOGY

Since playing a game is usually a voluntary activity, designers cannot force the player to act in a predetermined manner. Instead, one can only try to motivate the player; hence, psychology of motivation is one of the fields of research foundational to game design. Both psychology and game design literature usually divide motivations into extrinsic ones (e.g, scoring, leaderboards, rewards) and intrinsic ones (e.g., needs for competence and autonomy) [36, 37, 72]. The focus of this review is on intrinsic motivation, as it is less straightforward to support through game design and operationalize as AI code.

In the following, we review central research on intrinsic (player) motivations and player types. The terms motivation and type are sometimes used interchangeably. We would like to make the distinction that research on player motivation typically identifies core motivation dimensions such as curiosity or immersion, while a "player type" represents a label given to a cluster or class of players in a multidimensional motivation space. Our treatment leans heavily on the fairly recent meta-synthesis of player type research by Hamari and Tuunanen [28], augmented with non-game-specific psychology research.

Competence, autonomy, relatedness

One of the dominant intrinsic motivation theories is Self-Determination Theory (SDT), which posits that humans have three central needs: feeling of competence (e.g., taking on and mastering challenges), feeling of autonomy, and feeling of social relatedness [73]. SDT is used in various fields such as education, sports, and physical exercise, and its three needs have also been found to predict game enjoyment and intention to play in the future [74].

Further evidence of Self-Determination Theory's wide applicability is provided by the three studies by Sheldon et al. [83]. They asked the participants to think of the "most satisfying events" of their lives and then rate the salience of 10 needs identified in the psychological literature, using Likert-scale answers to statements like "During this event I felt a sense of contact with people who care for me, and whom I care for." In the results, competence, autonomy, and relatedness were consistently among the top 4 needs. Thus, we have selected them as the first three needs to be included in Table 2.

Curiosity, novelty, and interest

In addition to Self-Determination Theory, a frequently discussed intrinsic motivation in both games, learning, and artificial intelligence is curiosity, included as the fourth motivation in our Table 2. Its importance was highlighted already in the perhaps earliest empirical psychological study on intrinsic motivation and games by Malone [48]. However, later psychological research views curiosity as a personality trait that modulates the feeling of interest, which is elicited through appraisals of novelty-complexity and comprehensibility [85]. According to this theory, we are interested in, e.g., music that is novel and/or complex enough to spark our curiosity, but not incomprehensibly complex or novel. As Silvia [85] puts it, *new and comprehensible works are interesting; new and incomprehensible things are confusing.* This explains how musicians or music enthusiasts find pleasure in musical styles such as free jazz that may seem as incomprehensible and off-putting to a layperson. Similar results on novelty were also recently obtained in educational games by Lomas et al. [47].

In the Sheldon et al. [83] satisfying event experiments discussed in the previous section, curiosity/novelty also appeared high in the form of their pleasure-stimulation construct, which was rated using items such as "That I was experiencing new sensations and activities." Related constructs are also common in many player typologies [28].

Immersion

In his often cited study, Yee [96] identified three overarching motivational components: Achievement, Social, and Immersion. As Yee's achivement and social motivations overlap considerably with Self-Determination Theory's competence and relatedness, we have not included them as separate components in Table 2.

Yee's Immersion component comprises the subcomponents discovery, role-playing, customization, and escapism. Except for discovery, these are not well explained by the SDT or curiosity/novelty motivations, and they are also not directly related to extrinsic reinforcement. Thus, they would warrant a new category in Table 2. However, this is omitted as we found no papers with computational models of immersion.

Domination

The five key motivations discussed so far (competence, autonomy, social relatedness, curiosity/novelty, immersion) align well with the comprehensive meta-synthesis of player type research by Hamari and Tuunanen [28], who propose that player type and motivation research could be synthesized into the five dimensions of achievement, exploration, sociability, immersion, and domination.

The only component that stands out in the comparison is domination. We interpret domination as overlapping with SDT's autonomy, although the overlap is only partial – to be autonomous means that one is not dominated by others, but it does not imply exerting influence on others. Fascinatingly, domination was also studied by Sheldon et al. [83], whose Popularity-Influence scale included items like "I strongly influenced others' beliefs and behavior." and "I had strong impact on what other people did". However, Popularity-Influence was only the 9th most salient need within the participants' most satisfying experiences, way below competence, relatedness, or autonomy. Further, as we did not find domination-specific research in AI and player modeling, we have not included it as its own component in Table 2.

Summary and discussion

Naturally, the four key motivations listed on the left in Table 2 only represent one possible high-level coding of the various motivations discussed in the literature. Although motivations and needs can in principle be categorized with arbitrary granularity, and each new dataset might reveal a different motivational structure, it appears that player motivation research has reached something of a saturation point; the same high-level constructs such as Self-Determination Theory's competence, autonomy, and social relatedness are repeating in many studies in slightly varied forms. Thus, we are confident that we have included at least the most essential motivations.

Various alternative motivation models also exist. For instance, Heeter et al. [29] test the validity of Elliot and McGregor's [19] achievement goal framework in the context of games. They separate achievement goals into mastery and performance; a mastery-seeking person is motivated to develop competence regardless of others, whereas a person with performance goals seeks to demonstrate competence to others and avoids displaying incompetence. Other much cited player typologies and motivation models include Bartle's early player typology of achievers, explorers, socializers, and killers [6], Lazzaro's types of fun [43], and the neurobiologically inspired Brainhex player satisfaction model [61]. Brainhex divides players into seven archetypes: Seeker, Survivor, Daredevil, Mastermind, Conqueror, Socializer, and Achiever, which are largely in agreement with other models included the Hamari and Tuunanen meta-synthesis discussed above [28]. Lazzaro [43] proposes four types of fun: hard fun, easy fun, people fun, and serious fun. Hard fun is related to competence/achievement motivations, easy fun to curiosity and exploration, and people fun to social relatedness. Lazzaro [43] defines serious fun as "play as therapy", changing how players think, feel or behave, which is beyond our focus on basic psychological needs.

INTRINSIC MOTIVATION IN ARTIFICIAL INTELLIGENCE

There exists a growing body of research on intrinsic motivation in artificial intelligence, in particular in the domain of Reinforcement Learning (RL). The research dates back to Schmidhuber's early work on curiosity in RL [78, 79] and the more general intrinsically motivated RL formulation of Singh et al. [86]. This section reviews the field, with a summary provided in the middle column of Table 2

The concept of *reinforcement* bridges between AI and psychology and contributes to a unifying view of both extrinsic and intrinsic motivation. Both reinforcement learning and other AI methods usually employ some form of a reward function to maximize, such as a game score, or an action cost to minimize. This is analogical to the psychological concept of reinforcement, i.e., rewards and punishment. The term originates from early behavioral psychology, which focused purely on extrinsic reinforcement such as food pellets given to animal subjects. Although later psychological literature on intrinsic motivation avoids using the term reinforcement, intrinsic motivation can nevertheless be considered as reinforcement arising from within an organism [15, 86, 58].

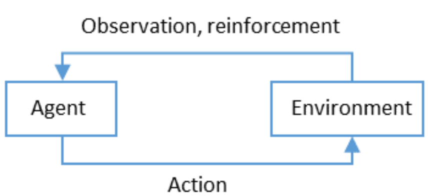

Figure 1. The classic Reinforcement Learning agent-environment loop.

In traditional reinforcement learning, an agent observes the environment, acts, and receives a reward/reinforcement, as illustrated in Figure 1. The reward is typically determined by a task-specific reward function. For example, there might be a positive reward for finding food in a maze, and a small negative reward (i.e., punishment) for moving. Reinforcement learning methods aim to maximize the expected future cumulative reward, which in this case would result in the agent learning to search for food using minimal movement.

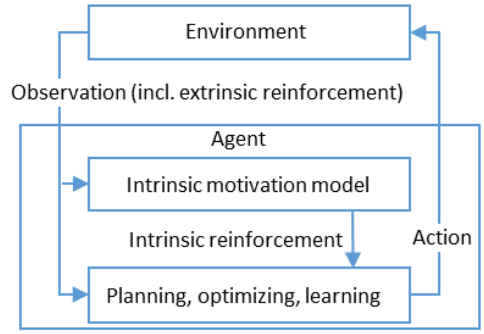

Figure 2. Intrinsic motivation as a layer that translates observations – including possible extrinsic reinforcement – into intrinsic reinforcement that is optimized by the agent.

In intrinsically motivated reinforcement learning, the reinforcement originate from within the agent/organism, and the extrinsic rewards no longer directly guide the learning [86]. This conceptual model is illustrated in Figure 2. Essentially, an intrinsic motivation layer translates observations and extrinsic reinforcement signals such as game score into intrinsic reinforcement that is then optimized through traditional RL. Our model is simplified from Singh et al. [86], where the environment is divided into an internal and external environment; the internal environment translates the agent's decisions into actions, and the sensations from the external environment into internal states and rewards observed by the agent. We omit this extra detail as the division between the internal and external environment is neither always clear nor necessary. Also, from an embodied and phenomenological perspective, it can be argued that an agent should observe/sense both the external environment and internal/bodily sensations as a whole.

As an example of how the mapping from extrinsic to intrinsic reinforcement works, consider that Skinner's early animal studies found that motivation to act is not simply proportional to an extrinsic reward; instead, random or otherwise unpredictable rewards yield strongest motivation [15], an effect that is exploited by the lottery mechanics of many modern games [13, 45]. Later research has also uncovered parts of the underlying neurophysiological mechanisms – it is known that dopamine plays a key role in motivation, and dopamine response in monkey brains has been observed to be proportional to the difference between actual and predicted reward [81]. Considering the architecture of Figure 2, the prediction and differencing would be computed within the intrinsic motivation model, and the intrinsic reinforcement signal would then model dopamine release, reinforcing the exploration of behaviors that yield unpredictable and novel results. This in turn can be considered a simple implementation of the intrinsic drive of curiosity, guiding an agent or organism to learn and explore widely and avoid getting stuck in a local optimum. Similar ideas are implemented in many recent AI algorithms [87, 8, 34, 33, 2, 66, 90].

From motivation to emotion

As reviewed recently by Moerland et al. [58], the intrinsically motivated reinforcement learning framework can also be interpreted as implementing emotions in a way compatible with the appraisal theory of emotions, which posits that emotions are elicited as combinations of evaluations (appraisals) of events and situations [70]. Practically all intrinsically motivated reinforcement learning systems as well as other biologically inspired cognitive architectures implement one or more appraisals such as the novelty/unexpectedness evaluation discussed above. In the following, we use the term *computational appraisal* to denote such appraisals implemented as code. These are then combined and encoded as the intrinsic reinforcement maximized by a learner or a search/planning/optimization method [4, 58, 21]. Ultimately, positive emotions are treated as intrinsic rewards, and negative emotions as intrinsic punishment. Although Moerland et al. [58] also identify four other key roles for emotion than reward manipulation, the other roles are more related to technical details of how to optimize the intrinsic rewards within a specific class of learning algorithms, e.g., by using a higher learning rate to adapt faster to life-threatening situations.

Different models have been proposed about which appraisals contribute to which emotions, and the intricate relationships between motivation and emotion are yet to be fully uncovered in psychology (e.g., [92]). One clear connection is offered by Lazarus [42]: In his structural model of appraisal, so called primary appraisals comprise evaluations of motivational relevance and motivational congruence. Motivational relevance evaluation reflects the situation against the individual's needs, whereas motivational congruence denotes evaluating the consistency of the situation with the individual's goals. Considering this dichotomy, an intrinsically motivated game playing agent should implement motivational relevance appraisals based on its psychological needs, and motivational congruence appraisals related to extrinsic goals provided by the game such as completing the current game level.

Common computational appraisals

Computational appraisals directly linked to the intrinsic motivations of Table 2 include:

- *Empowerment/control/power/competence* (e.g., [75, 59, 22]): The computational model of empowerment, as first introduced by Klyubin et al. [41], denotes the degree of freedom that an agent has over the environment. An empowered agent prefers states where it will have the most control and also will be able to sense this control. Formally, empowerment is defined as the maximum amount of information that the agent could collect by performing a sequence of actions. Guckelsberger et al. [24] draw on psychology research to relate empowerment to both competence and autonomy. In the PSI cognitive architecture [5], there's a need/appraisal for competence, which is increased by each satisfaction of other needs such as thirst or hunger, and decreased by long periods of non-satisfaction.
- *Novelty/surprise/curiosity/(un-)certainty* (e.g., [87, 62, 8, 34, 2, 66]): These appraisals cause the agent to seek novel experiences. For example, the agent can be given an extra reward if it visits a previously non-visited state, or observes action outcomes that it did not predict, i.e., that conflict with the understanding it has built so far. Pathak et al. [66] add an intrinsic reward proportional to how hard it is for the agent to predict the consequences of its own actions. Houthooft et al. [34] used variational inference to measure information gain, persuading the agents to take actions which surprise them and cause large updates of their learned dynamics model. The PSI cognitive architecture [5] defines a need for certainty about the agent's knowledge; low certainty triggers the agent to explore its environment.
- *Loneliness/Social affiliation* ([76, 5, 18]) Although the need for social relatedness is perhaps among the hardest intrinsic motivations to implement as computational appraisals, there are some practical examples. In Salichs et al. [76], getting kicked or stolen from increase the agent's loneliness, and being given to decreases loneliness. It should be noted that gifting is also one of the most common social mechanics in games [1]. The PSI cognitive architecture [5, 18] also includes the need for social affiliation. The corresponding appraisal is increased by other agents' signals of legitimacy such as a smile or a clap on the shoulder, and decreased by signals of nonaffiliation.

The review by Moerland et al. [58] also lists other common computational appraisals, including intrinsic pleasantness and social accountability. Intrinsic pleasantness denotes an appraisal of the pleasantness of a stimulus independent of an extrinsic goal [77], which might seem difficult to implement computationally. Indeed, practical intrinsic pleasantness implementations are not always well motivated by emotion theory and they can be task and goal-specific. In the maze task of Marinier et al. [49], directions leading to walls have low intrinsic pleasantness. Sequeira et al. [82] denote intrinsic pleasantness simply as valence, and state that it refers to the biological significance for the organism, which is close to Lazarus' motivational relevance [42]. Sequeira et al. [82] implement the valence appraisal as the ratio of the current extrinsic reward to the total expected future reward.

Social accountability is an example of a complex cognitive appraisal related to social emotions. As noted by Moerland et al. [58], it is also an example of an appraisal that requires some other AI techniques in addition to the basic intrinsically motivated RL framework, which probably explains why it has received less attention. It is however a highly relevant modulator for the need of social relatedness, as understanding who was responsible for an event affects who we like and want to be affiliated with.

An alternative overview of computationally implemented intrinsic motivations is given by Baldassare and Mirolli [4] who divide the implementations into prediction-based, competence-based, and novelty-based ones. On the other hand, Oudeyer and Kaplan [64] propose a division into knowledge-based, competence-based, and morphological models.

Many intrinsically motivated systems also implement *homeostatic* variables, i.e., low-level existential needs such as hunger or thirst, which also modulate the intrinsic reinforcement.

The division between homeostatic variables and emotional appraisals is not clear, however. For example, Moerland et al. [58] categorize loneliness as a homeostatic variable instead of an appraisal.

Summary and discussion

As pointed out by Moerland et al. [58], translating abstract cognitive concepts to computational models is often not straightforward, which probably explains why the technical literature on intrinsic motivation is focused on relatively simple motivations and appraisals such as competence and curiosity. Another explanation for this is that intrinsically motivated AI does not always aim to model human psychological needs or human behavior; instead, the goal is often to engineer more autonomous agents which learn more efficiently by e.g. exploring their environment, especially when extrinsic rewards are sparse or otherwise provide only a weak supervisory signal for the learning process. An example of this in classic computer games is Montezuma's Revenge, which an intrinsically motivated, exploratory agent can solve more efficiently [8]. Yet another use for intrinsically motivated RL is proposed by Sukhbaatar et al. [89], who used a Goal Generative Adversarial Network (Goal GAN) to model the interplay of a coach agent and a learning agent. Their intrinsic reward structure guided the coach to come up with appropriately difficult challenges.

Looking at the psychological and technical literature as a whole, terminology appears convoluted; same terms are used for different purposes, and different terms are used for the same purpose. The fields could certainly benefit from more crosstalk and common vocabulary. Motivational relevance and motivational congruence concepts are in particular often mixed. For example, in Sequeira et al. [82], motivational relevance is proportional to the distance of the agent of its perceived goals instead of psychological needs.

INTRINSIC MOTIVATION IN PLAYER MODELING

This section reviews how the motivations and computational appraisals discussed above have been applied in the domain of player modeling and simulation-based game testing.

Competence and autonomy

Many of the papers featuring intrinsically motivated game-playing agents discuss and implement multiple motivations. Competence and autonomy motivations in particular appear often entangled through appraisals such as empowerment.

An example of a computational appraisal for competence is given by Merrick [51], extending previous work on curiosity [53]. Competence is modeled as having an inverted U relation to the estimated error of the agent's current action-value function model. Thus, the competence appraisal is low when the agent predicts the future rewards of actions either very accurately or very inaccurately. In other words, the appraisal is high when there's a moderate learning error.

Related to competence, Merrick and Shafi [55] proposed a computational model of achievement and power motivations for goal selection. Their base appraisal is the probability of success, which is then transformed nonlinearly so that the agent may either require a high probability of success to be motivated (avoidance of failure, needing successes for feeling competent), or favor a moderate probability, only ignoring very improbable or highly probable successes (achievement motivation, seeking challenges). Power motivation is non-linearly proportional to the reward associated with a goal; power-motivated agents seek high-payoff goals. Merrick and Shafi [55] tested their model using reflexive agents in different scenarios. Reflexive agents select actions based on the current percept of the environment only [71].

In a continuation study, Merrick [52] used the same computational model of motivation in order to highlight the role of motivation in decision making. They demonstrated how different behaviors of agents emerged in a game theoretic setting by different parameters of the computational model. Merrick defined different agents by changing the parameters, and then computed the optimal motivating incentive (Ω). Subsequently, they computed the subjective incentive I_t which determines the agent's perception of the explicit incentive (payoff) as $I_t = V_{\max} - |V_t - \Omega|$, where $V_{\max}$ and V_t denote the maximum possible explicit incentive (payoff) and the explicit incentive received for executing behavior B_{t-1}, respectively. Agents use this subjective incentive to update the probability of a specific behavior. Merrick tested the agents in social dilemma games with mixed-motive environments in which agents had to choose between being cooperative and defecting. The results showed that agents changed their strategy over time with respect to their optimal motivating incentive and their opponent's behavior.

Mariusdottir et al. [50] implemented a meta-controller which drives the agent to tasks at a level of complexity suitable for its skill level. The level complexity is defined as the minimum skill that the agent needs for success; this is measured through trials with different skill levels. They tested the method on a role-playing game where the skill level of the agent is represented by the character's attributes.

Cai et al. [14] proposed a computational model of competence need based on PSI theory. They applied it for controlling an agent living in a game environment inspired by Minecraft. Competence was computed based on the number of the agent's successful and failed actions.

Anthony, Polani and Nehaniv [3] have evaluated empowerment as intrinsic drive for general game-playing agents. To model play under bounded rationality, they have employed the information bottleneck method [91] to find qualitatively different behavioural strategies over long time horizons. Their agents successfully identified latent features from the dynamics of Sokoban and Pac-Man-like games and selected appropriate proto-strategies without access to extrinsic game goals.

In the context of predicting player experience, Guckelsberger et al. [24] use the computational model of empowerment and AI agent gameplay data to measure empowerment in an infinite runner game and produce levels with predefined empowerment. In their user study, they found that high or low empowerment levels, measured by simulated agents, was reflected on coarse player experience dimensions such as challenge, involvement, and engagement. Based on psychology and game design literature, they hypothesise that empowerment more directly relates to a human player's experience of effectance, (outcome) uncertainty and perceived control. They also discuss the relationship of empowerment to both Self-Determination Theory's competence and autonomy.

Halim et al. [27] estimate the entertainment value of a game level using an inverted U mapping of the game's learnability, favoring not too hard and not too easy levels. Learnability is evaluated as the number of iterations of genetic optimization it takes to train an agent to win the game against other agents.

Curiosity
Merrick and Maher [53] implemented novelty-seeking in non-player characters and showed that motivated NPCs can evolve and adapt to new situations. Novelty is calculated using Stanley's habituation model [88]. Based on this model, novelty of a specific state decreases with occurence of that state and increases by non-occurence of it. This was then mapped to an inverted U curve in order to calculate an interest appraisal that was used as the reward for the agent.

Based on PSI theory, Cai et al. [14] proposed a computational model of certainty which was calculated according to how recently an object had been observed by the agent.

Some work on general video game AI have used curiosity as a heuristic for improving an agent's performance. Park and Kim [65] augmented MCTS with an influence map; for building the influence map, the agent is directed towards unseen game objects during simulation. Guerrero-Romero et al. [25] added various heuristics in addition to maximizing winning, such as maximizing exploration and interaction with different game elements. The results showed that adding these heuristics improved agent performance and each heuristic had a different effect.

Relatedness
The achievement and power motivation study by Merrick and Shafi [55] discussed above also proposed a computational model of affiliation motivation. Similar to their power motivation, the affiliation motivation is also based on the rewards associated with goals. Affiliation-motivated agents seek low-reward goals in order to avoid competition with power-motivated agents.

Guckelsberger et al. [23] use coupled empowerment to design a general companion NPC which relates to the player in a supportive manner. Maximising coupled empowerment, a multi-agent extension of empowerment, makes an agent choose actions which maintain the empowerment of a coupled agent, and consider the effect of this coupled agent's behavior on the performing agent's own empowerment. As a result, the companion follows and protects the player, but also ensures its own survival.

The model of Cai et al. [14] evaluates the satisfaction of the need for affiliation through the number of friends that are near the agent in the game environment.

Other motivations and approaches
Bostan [11] proposed a motivational framework for analyzing and predicting player and virtual agent behavior in games, based on 27 psychological needs from Murray's early theory [60]. Bostan provides formulas for determining the probability of various behaviors; thus, the framework can be used both for analyzing playtraces and synthesizing agent behavior. The probabilities are based on primary, secondary, and opposing needs, expectancy value, and goal valence. However, no experimental results were provided.

Forgette and Katchabaw [20] utilized the theory of Reiss [69, 68] in which motives provoke people to perform tasks and affect a person's emotion, perception, and outcome behavior. The theory encompasses 16 basic motives including power, curiosity, independence, status, social contact, vengeance, honor, idealism, physical exercise, romance, family, order, hunger, acceptance, tranquility, and saving. Forgette and Katchabaw [20] let the level of motivations drive action selection of reinforcement learning agents, selecting one dominant motivation at a time, and attempting to keep all computational appraisals within predetermined target ranges.

Summary and discussion
In summary, player modeling and simulation-based game testing using intrinsically motivated agents appears to still be a young field dominated by a few prolific authors such as Merrick [53, 51, 55, 52, 54].

In general, a common way of computing appraisals related to motivations and emotion is to utilize fairly simple variables such as predictability or magnitude of rewards, and then use a nonlinear transformation to produce, e.g., an inverted U curve. Sometimes, simple rules work, such as "affiliation-motivated agents seek low rewards". However, one may ask whether this is valid generally or only in the simplified social structure and agent population of a specific experiment?

Another basic tool is to have appraisals not evaluated instantaneously based on the agent's current state, action, and observations, but instead have some sort of low-pass filter or gradual accumulation over time. In Forgette and Katchabaw [20], the motive values decay exponentially until increased by the agent's actions. Similarly, the PSI architecture employs "tanks" with inflow and outflow affected by the agent's experiences. The tank levels are utilized as appraisals related to needs; a too high or low value causes the corresponding need to dominate in action selection.

Unfortunately, similar to the broader field of intrinsically motivated AI, the terminology used is inconsistent. For example, Merrick's competence appraisal [51] is based on the unpredictability of rewards, i.e., how big an update is made to the predictor model based on new observations. On the other hand, the first principle of Schmidhuber's theory of artificial curiosity is that one should generate a curiosity reward based on exactly the same signal [80]. Further, Halim et al. [27] frame their work as motivated by Schmidhuber's theory [80], while their actual computational appraisal (i.e., learning time) is more related to competence/challenge.

Another point of critique we must raise is that the reviewed papers rarely evaluate the work beyond simply demonstrating that different model parameters produce different behavior. The work seems promising, but validation with real player data is called for. For example, if a motivation and emotion model is supposed to make a game-playing agent more believable – and thus more suitable for simulation-based game testing – believability should be both clearly defined and quantified in a user study. Moreover, there is a clear need for future work that demonstrates and validates motivation models and computational appraisals in more complex games and simulations. So far, research has focused on simple games and simulation environments such as 2D mazes.

OPEN AREAS

Although a considerable body of literature exists on intrinsically motivated agents, the technology has only rarely been applied in player modeling and simulation-based game testing. Generating agents with a wider variety of motivations is in particular an open area. Presently, research has mostly focused on combinations of only few motivations, in particular curiosity, competence, and empowerment. Social relatedness and immersion in particular remain underexplored.

In our literature search, we found vastly more player modeling research that utilizes real players and psychometric or physiological data gathering than research on game-playing agents with computational models of motivation and emotion. In the future, research should probably strive to combine these two topics, using player data to validate and improve the human-likeness of simulated agents. Naturally, the more complex the computational model, the more and better data is needed to adjust the model parameters and validate the predictions.

Fortunately, online games have the potential to generate massive amounts of data; related to this, researchers should find ways to validate and improve the models primarily on in-game behavior data, as such data is far more easier to gather without disturbing the player's game experience. Clear examples of behavioral metrics that could be utilized include win ratio, average score, frequencies of different actions such as killing enemies or collecting treasure, and traces of player state variables such as spatial position. It is less clear, however, how the metrics reflect the motivations. The present research on intrinsically motivated agents has perhaps selected the evaluation metrics more based on what metrics show the effect of manipulating the motivations, and less based on what metrics game designers and QA teams find most relevant – a further question for future work is how to better include the stakeholders.

Another important topic is defining clear metrics that can be used for evaluating game designs, and that could be computed based on data generated by simulated players. Some of such metrics are obvious, such as the win rates of different weapons in a competitive multiplayer game; in a balanced game, no weapon should have vastly greater win rate. On the other hand, it is less straightforward to develop metrics for a story-driven single player game. Although basic appraisals such as surprisal can probably be computed from image and natural language data with modern deep learning techniques, understanding and simulating the complex emotions evoked by a game's narrative remain beyond current techniques.

CONCLUSION

We have overviewed the common intrinsic motivations and psychological needs discussed in the literature on motivation and games. Subsequently, we have reviewed how these motivations have been implemented in intelligent agents. A primary strategy is to have an intrinsic motivation module that translates the agent's observations and extrinsic rewards into intrinsic rewards, which the agent then attempts to maximize. In effect, such an intrinsic motivation module usually implements emotions through one or more computational appraisals such as an evaluation of the predictability of the reward. The appraisals are then combined and encoded in the intrinsic reinforcement signal; in essence, this means that positive emotions are treated as intrinsic rewards, and negative emotions are treated as punishment that the agents avoid.

Of the common intrinsic motivations – competence, autonomy, social relatedness, curiosity, immersion, domination – curiosity appears to be the most often utilized one both in general AI and game-playing agents, implemented through appraisals of unpredictability of the rewards or observations. Together with the need for competence and challenges, curiosity helps both real organisms and simulated agents explore and learn even if the extrinsic rewards are rare or otherwise do not provide strong guidance. Another common computational appraisal is information-theoretic empowerment, denoting the magnitude of change the agent can have in its sensory inputs through its actions. Empowerment has been suggested to be related to both competence and autonomy [24], and it may also be linked to the domination motivations identified in games, as being able to dominate others enables new degrees of freedom for controlling a social environment.

Work on social relatedness and in particular immersion and domination is sparse, with only a few examples. In general, despite the prevalence of the term "intrinsic motivation", intrinsically motivated AI seems to in practice focus more on appraisal theories of emotion than intrinsic motivation theories such as Self-Determination Theory. This is understandable, as appraisal theory provides more clear concepts that can be implemented as AI code, although it might be less well known in the game research community than player type research or Self-Determination Theory.

In the domain of player modeling, research has utilized both explicit motivation models based on computational appraisals, and implicit models learned from player data. Explicit models appear less prevalent; in the end, we found surprisingly few papers to include in this review. What also appears to be missing is a combination of both approaches: explicit models validated and fine-tuned based on real player data. We believe that such models have the potential to provide both the high accuracy of data-driven models and high versatility and generalization capabilities of data-free models. Explicit computational appraisals also have the benefit of acting both as behavior drivers and as measures of the agent's affective state. Thus, they could be used for both testing for player behavior and player experience, which could perhaps be combined with or substituted for the expressive but labor-intensive physiological player experience research methods such as Biometric Storyboards [56].

To enable developing and validating better computational models of motivation and emotion, closer collaboration of AI and player experience researchers is called for, with the goal of compiling rich datasets and benchmarks. Such datasets should include time-stamped data streams with enough temporal resolution, e.g., gameplay videos, game event logs, and affect signals such as Galvanic Skin Response, Heart-rate Variability, and player facial expressions. Further, the datasets should be collected from games that allow the integration of custom AI agents, e.g., through the OpenAI Gym interface [12]. To the best of our knowledge, no current publicly available dataset satisfies all the criteria.

ACKNOWLEDGEMENTS

We thank the anonymous reviewers for their valuable comments and insight. The suggestions and comments of Jussi Jokinen and Christoph Salge were also invaluable. Hämäläinen and Takatalo are supported by Academy of Finland grants 299358 and 305737. Guckelsberger is supported by EPSRC grant EP/L015846/1 (IGGI).

REFERENCES

1. Game design patterns for building friendships. `http://www.lostgarden.com/2017/01/game-design-patterns-for-building.html`. (????). Accessed: 2017-09-16.
2. Joshua Achiam and Shankar Sastry. 2017. Surprise-Based Intrinsic Motivation for Deep Reinforcement Learning. *arXiv preprint arXiv:1703.01732* (2017).
3. Tom Anthony, Daniel Polani, and Chrystopher L Nehaniv. 2014. General self-motivation and strategy identification: Case studies based on Sokoban and Pac-Man. *IEEE Transactions on Computational Intelligence and AI in Games* 6, 1 (2014), 1–17.
4. Gianluca Baldassarre and Marco Mirolli. 2013. Intrinsically motivated learning systems: an overview. In *Intrinsically motivated learning in natural and artificial systems*. Springer, 1–14.
5. Christina Bartl and Dietrich Dörner. 1998. PSI: A theory of the integration of cognition, emotion and motivation. In *Proceedings of the 2nd European Conference on Cognitive Modelling*. DTIC Document, 66–73.
6. Richard Bartle. 1996. Hearts, clubs, diamonds, spades: Players who suit MUDs. *Journal of MUD research* 1, 1 (1996), 19.
7. Andrew G Barto. 2013. Intrinsic motivation and reinforcement learning. In *Intrinsically motivated learning in natural and artificial systems*. Springer, 17–47.
8. Marc Bellemare, Sriram Srinivasan, Georg Ostrovski, Tom Schaul, David Saxton, and Remi Munos. 2016. Unifying count-based exploration and intrinsic motivation. In *Advances in Neural Information Processing Systems*. 1471–1479.
9. Max V Birk, Regan L Mandryk, Matthew K Miller, and Kathrin M Gerling. 2015a. How self-esteem shapes our interactions with play technologies. In *Proceedings of the 2015 Annual Symposium on Computer-Human Interaction in Play*. ACM, 35–45.
10. Max V Birk, Dereck Toker, Regan L Mandryk, and Cristina Conati. 2015b. Modeling Motivation in a Social Network Game using Player-Centric Traits and Personality Traits. In *International Conference on User Modeling, Adaptation, and Personalization*. Springer, 18–30.
11. Barbaros Bostan. 2010. A motivational framework for analyzing player and virtual agent behavior. *Entertainment Computing* 1, 3 (2010), 139–146.
12. Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. 2016. OpenAI Gym. (2016).
13. Charles Butler. 2015. Applied behavioral economics: a game designer's perspective. In *Gamification in Education and Business*. Springer, 81–104.
14. Zhenhua Cai, Ben Goertzel, Changle Zhou, Deheng Huang, Shujing Ke, Gino Yu, and Min Jiang. 2013. OpenPsi: a novel computational affective model and its application in video games. *Engineering Applications of Artificial Intelligence* 26, 1 (2013), 1–12.
15. Neil R Carlson, Harold L Miller, Donald S Heth, John W Donahoe, and G Neil Martin. 2013. *Psychology: Pearson New International Edition: The Science of Behavior*. Pearson Higher Ed.
16. Zhao Chen and Darvin Yi. 2017. The Game Imitation: Deep Supervised Convolutional Networks for Quick Video Game AI. *arXiv preprint arXiv:1702.05663* (2017).
17. Sam Devlin, Anastasija Anspoka, Nick Sephton, Peter I Cowling, and Jeff Rollason. 2016. Combining Gameplay Data With Monte Carlo Tree Search To Emulate Human Play. In *Twelfth Artificial Intelligence and Interactive Digital Entertainment Conference*.
18. Dietrich Dörner and C Dominik Güss. 2013. PSI: A computational architecture of cognition, motivation, and emotion. *Review of General Psychology* 17, 3 (2013), 297–317.
19. Andrew J Elliot and Holly A McGregor. 2001. A 2×2 achievement goal framework. *Journal of personality and social psychology* 80, 3 (2001), 501.
20. Jacquelyne Forgette and Michael Katchabaw. 2014. Enabling motivated believable agents with reinforcement learning. In *Games Media Entertainment (GEM), 2014 IEEE*. IEEE, 1–8.
21. Ben Goertzel, Ruiting Lian, Itamar Arel, Hugo De Garis, and Shuo Chen. 2010. A world survey of artificial brain projects, Part II: Biologically inspired cognitive architectures. *Neurocomputing* 74, 1 (2010), 30–49.

22. Karol Gregor, Danilo Jimenez Rezende, and Daan Wierstra. 2016. Variational Intrinsic Control. *arXiv preprint arXiv:1611.07507* (2016).
23. Christian Guckelsberger, Christoph Salge, and Simon Colton. 2016. Intrinsically Motivated General Companion NPCs via Coupled Empowerment Maximisation. In *Computational Intelligence and Games (CIG), 2016 IEEE Conference on*. IEEE, 1–8.
24. Christian Guckelsberger, Christoph Salge, Jeremy Gow, and Paul Cairns. 2017. Predicting Player Experience without the Player An Exploratory Study. In *Proc. CHI PLAY 2017*. ACM Press.
25. Cristina Guerrero-Romero, Annie Louis, and Diego Perez-Liebana. 2017. Beyond playing to win: Diversifying heuristics for GVGAI. In *Computational Intelligence and Games (CIG), 2017 IEEE Conference on*. IEEE, 118–125.
26. Matthew Guzdial, Nathan Sturtevant, and Boyang Li. 2016. Deep static and dynamic level analysis: A study on infinite mario. In *Third Experimental AI in Games Workshop*, Vol. 3.
27. Zahid Halim, Abdul Rauf Baig, and Kashif Zafar. 2014. Evolutionary search in the space of rules for creation of new two-player board games. *International Journal on Artificial Intelligence Tools* 23, 02 (2014), 1350028.
28. Juho Hamari and Janne Tuunanen. 2014. Player types: A meta-synthesis. *Transactions of the Digital Games Research Association* 1, 2 (2014).
29. Carrie Heeter, Yu-Hao Lee, Ben Medler, and Brian Magerko. 2011. Beyond player types: gaming achievement goal. In *Proceedings of the 2011 ACM SIGGRAPH symposium on video games*. ACM, 43–48.
30. Christoffer Holmgård, Antonios Liapis, Julian Togelius, and Georgios N Yannakakis. 2014a. Evolving personas for player decision modeling. In *Computational Intelligence and Games (CIG), 2014 IEEE Conference on*. IEEE, 1–8.
31. Christoffer Holmgård, Antonios Liapis, Julian Togelius, and Georgios N Yannakakis. 2014b. Generative agents for player decision modeling in games.. In *FDG*.
32. Christoffer Holmgård, Antonios Liapis, Julian Togelius, and Georgios N Yannakakis. 2015. Monte-carlo tree search for persona based player modeling. In *Eleventh Artificial Intelligence and Interactive Digital Entertainment Conference*.
33. Rein Houthooft, Xi Chen, Yan Duan, John Schulman, Filip De Turck, and Pieter Abbeel. 2016a. Curiosity-driven exploration in deep reinforcement learning via bayesian neural networks. *arXiv preprint arXiv:1605.09674* (2016).
34. Rein Houthooft, Xi Chen, Yan Duan, John Schulman, Filip De Turck, and Pieter Abbeel. 2016b. Vime: Variational information maximizing exploration. In *Advances in Neural Information Processing Systems*. 1109–1117.
35. Aaron Isaksen, Daniel Gopstein, and Andrew Nealen. 2015. Exploring Game Space Using Survival Analysis.. In *FDG*.
36. Karl M Kapp. 2013. *The gamification of learning and instruction fieldbook: Ideas into practice*. John Wiley & Sons.
37. Dennis L Kappen and Lennart E Nacke. 2013. The kaleidoscope of effective gamification: deconstructing gamification in business applications. In *Proceedings of the First International Conference on Gameful Design, Research, and Applications*. ACM, 119–122.
38. Ahmed Khalifa, Aaron Isaksen, Julian Togelius, and Andy Nealen. 2016a. Modifying MCTS for Human-Like General Video Game Playing.. In *IJCAI*. 2514–2520.
39. Ahmed Khalifa, Diego Perez-Liebana, Simon M Lucas, and Julian Togelius. 2016b. General video game level generation. In *Proceedings of the 2016 on Genetic and Evolutionary Computation Conference*. ACM, 253–259.
40. J Matias Kivikangas, Guillaume Chanel, Ben Cowley, Inger Ekman, Mikko Salminen, Simo Järvelä, and Niklas Ravaja. 2011. A review of the use of psychophysiological methods in game research. *journal of gaming & virtual worlds* 3, 3 (2011), 181–199.
41. Alexander S Klyubin, Daniel Polani, and Chrystopher L Nehaniv. 2005. Empowerment: A universal agent-centric measure of control. In *Evolutionary Computation, 2005. The 2005 IEEE Congress on*, Vol. 1. IEEE, 128–135.
42. Richard S Lazarus. 1991. Progress on a cognitive-motivational-relational theory of emotion. *American psychologist* 46, 8 (1991), 819.
43. Nicole Lazzaro. 2004. Why we play games: Four keys to more emotion without story. (2004).
44. Geoffrey Lee, Min Luo, Fabio Zambetta, and Xiaodong Li. 2014. Learning a super mario controller from examples of human play. In *Evolutionary Computation (CEC), 2014 IEEE Congress on*. IEEE, 1–8.
45. Chris Lewis, Noah Wardrip-Fruin, and Jim Whitehead. 2012. Motivational game design patterns of'ville games. In *Proceedings of the International Conference on the Foundations of Digital Games*. ACM, 172–179.
46. Jialin Liu, Julian Togelius, Diego Pérez-Liébana, and Simon M Lucas. 2017. Evolving Game Skill-Depth using General Video Game AI Agents. *arXiv preprint arXiv:1703.06275* (2017).
47. J Derek Lomas, Kenneth Koedinger, Nirmal Patel, Sharan Shodhan, Nikhil Poonwala, and Jodi L Forlizzi. 2017. Is Difficulty Overrated?: The Effects of Choice, Novelty and Suspense on Intrinsic Motivation in Educational Games. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. ACM, 1028–1039.

48. Thomas W Malone. 1981. Toward a theory of intrinsically motivating instruction. *Cognitive science* 5, 4 (1981), 333–369.

49. Robert P Marinier and John E Laird. 2008. Emotion-driven reinforcement learning. In *Proceedings of the Cognitive Science Society*, Vol. 30.

50. Thorey Mariusdottir, Vadim Bulitko, and Matthew Brown. 2015. Maximizing Flow as a Metacontrol in Angband. In *Eleventh Artificial Intelligence and Interactive Digital Entertainment Conference*.

51. Kathryn Merrick. 2008. Modeling motivation for adaptive nonplayer characters in dynamic computer game worlds. *Computers in Entertainment (CIE)* 5, 4 (2008), 5.

52. Kathryn Merrick. 2015. The role of implicit motives in strategic decision-making: computational models of motivated learning and the evolution of motivated agents. *Games* 6, 4 (2015), 604–636.

53. Kathryn Merrick and Mary Lou Maher. 2006. Motivated reinforcement learning for non-player characters in persistent computer game worlds. In *Proceedings of the 2006 ACM SIGCHI international conference on Advances in computer entertainment technology*. ACM, 3.

54. Kathryn E Merrick. 2016. *Computational Models of Motivation for Game-Playing Agents*. Springer.

55. Kathryn E Merrick and Kamran Shafi. 2011. Achievement, affiliation, and power: Motive profiles for artificial agents. *Adaptive Behavior* 19, 1 (2011), 40–62.

56. Pejman Mirza-Babaei, Lennart Nacke, Geraldine Fitzpatrick, Gareth White, Graham McAllister, and Nick Collins. 2012. Biometric storyboards: visualising game user research data. In *CHI'12 Extended Abstracts on Human Factors in Computing Systems*. ACM, 2315–2320.

57. Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, and others. 2015. Human-level control through deep reinforcement learning. *Nature* 518, 7540 (2015), 529–533.

58. Thomas M Moerland, Joost Broekens, and Catholijn M Jonker. 2017. Emotion in Reinforcement Learning Agents and Robots: A Survey. *arXiv preprint arXiv:1705.05172* (2017).

59. Shakir Mohamed and Danilo Jimenez Rezende. 2015. Variational information maximisation for intrinsically motivated reinforcement learning. In *Advances in neural information processing systems*. 2125–2133.

60. Henry Alexander Murray. 1938. Explorations in personality. (1938).

61. Lennart E Nacke, Chris Bateman, and Regan L Mandryk. 2014. BrainHex: A neurobiological gamer typology survey. *Entertainment computing* 5, 1 (2014), 55–62.

62. Junhyuk Oh, Xiaoxiao Guo, Honglak Lee, Richard L Lewis, and Satinder Singh. 2015. Action-conditional video prediction using deep networks in atari games. In *Advances in Neural Information Processing Systems*. 2863–2871.

63. Juan Ortega, Noor Shaker, Julian Togelius, and Georgios N Yannakakis. 2013. Imitating human playing styles in super mario bros. *Entertainment Computing* 4, 2 (2013), 93–104.

64. Pierre-Yves Oudeyer and Frederic Kaplan. 2008. How can we define intrinsic motivation?. In *Proceedings of the 8th International Conference on Epigenetic Robotics: Modeling Cognitive Development in Robotic Systems*. Lund University Cognitive Studies, Lund: LUCS, Brighton.

65. Hyunsoo Park and Kyung-Joong Kim. 2015. Mcts with influence map for general video game playing. In *Computational Intelligence and Games (CIG), 2015 IEEE Conference on*. IEEE, 534–535.

66. Deepak Pathak, Pulkit Agrawal, Alexei A Efros, and Trevor Darrell. 2017. Curiosity-driven exploration by self-supervised prediction. *arXiv preprint arXiv:1705.05363* (2017).

67. Luong Huu Phuc, Kanazawa Naoto, and Ikeda Kokolo. 2017. Learning human-like behaviors using neuroevolution with statistical penalties. In *Computational Intelligence and Games (CIG), 2017 IEEE Conference on*. IEEE, 207–214.

68. Steven Reiss. 2004. Multifaceted nature of intrinsic motivation: The theory of 16 basic desires. *Review of general psychology* 8, 3 (2004), 179.

69. Steven Reiss and Susan M Havercamp. 1998. Toward a comprehensive assessment of fundamental motivation: Factor structure of the Reiss Profiles. *Psychological Assessment* 10, 2 (1998), 97.

70. Ira J Roseman and Craig A Smith. 2001. Appraisal theory. *Appraisal processes in emotion: Theory, methods, research* (2001), 3–19.

71. Stuart J Russell and Peter Norvig. 2002. *Artificial intelligence: a modern approach (International Edition)*. {Pearson US Imports & PHIPEs}. 48 pages.

72. Richard M Ryan and Edward L Deci. 2000a. Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary educational psychology* 25, 1 (2000), 54–67.

73. Richard M Ryan and Edward L Deci. 2000b. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist* 55, 1 (2000), 68.

74. Richard M Ryan, C Scott Rigby, and Andrew Przybylski. 2006. The motivational pull of video games: A self-determination theory approach. *Motivation and emotion* 30, 4 (2006), 344–360.

75. Christoph Salge, Cornelius Glackin, and Daniel Polani. 2014. Empowerment–an introduction. In *Guided Self-Organization: Inception*. Springer, 67–114.
76. Miguel A Salichs and Maria Malfaz. 2012. A new approach to modeling emotions and their use on a decision-making system for artificial agents. *IEEE Transactions on affective computing* 3, 1 (2012), 56–68.
77. Klaus R Scherer. 2001. Appraisal considered as a process of multilevel sequential checking. *Appraisal processes in emotion: Theory, methods, research* 92, 120 (2001), 57.
78. Jürgen Schmidhuber. 1991a. Curious model-building control systems. In *Neural Networks, 1991. 1991 IEEE International Joint Conference on*. IEEE, 1458–1463.
79. Jürgen Schmidhuber. 1991b. A possibility for implementing curiosity and boredom in model-building neural controllers. In *From animals to animats: proceedings of the first international conference on simulation of adaptive behavior (SAB90)*.
80. Jürgen Schmidhuber. 2006. Developmental robotics, optimal artificial curiosity, creativity, music, and the fine arts. *Connection Science* 18, 2 (2006), 173–187.
81. Wolfram Schultz, Peter Dayan, and P Read Montague. 1997. A neural substrate of prediction and reward. *Science* 275, 5306 (1997), 1593–1599.
82. Pedro Sequeira, Francisco S Melo, and Ana Paiva. 2011. Emotion-based intrinsic motivation for reinforcement learning agents. In *International Conference on Affective Computing and Intelligent Interaction*. Springer, 326–336.
83. Kennon M Sheldon, Andrew J Elliot, Youngmee Kim, and Tim Kasser. 2001. What is satisfying about satisfying events? Testing 10 candidate psychological needs. *Journal of personality and social psychology* 80, 2 (2001), 325.
84. David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, and others. 2016. Mastering the game of Go with deep neural networks and tree search. *Nature* 529, 7587 (2016), 484–489.
85. Paul J Silvia. 2008. Interest-The curious emotion. *Current Directions in Psychological Science* 17, 1 (2008), 57–60.
86. Satinder P Singh, Andrew G Barto, and Nuttapong Chentanez. 2004. Intrinsically motivated reinforcement learning. In *Advances in neural information processing systems*. 1281–1288.
87. Bradly C Stadie, Sergey Levine, and Pieter Abbeel. 2015. Incentivizing exploration in reinforcement learning with deep predictive models. *arXiv preprint arXiv:1507.00814* (2015).
88. James C Stanley. 1976. Computer simulation of a model of habituation. *Nature* 261, 5556 (1976), 146–148.
89. Sainbayar Sukhbaatar, Ilya Kostrikov, Arthur Szlam, and Rob Fergus. 2017. Intrinsic Motivation and Automatic Curricula via Asymmetric Self-Play. *arXiv preprint arXiv:1703.05407* (2017).
90. Stas Tiomkin, Daniel Polani, and Naftali Tishby. 2017. Control Capacity of Partially Observable Dynamic Systems in Continuous Time. *arXiv preprint arXiv:1701.04984* (2017).
91. Naftali Tishby, Fernando C Pereira, and William Bialek. 2000. The information bottleneck method. *arXiv preprint physics/0004057* (2000).
92. Leen Vandercammen, Joeri Hofmans, and Peter Theuns. 2014. Relating specific emotions to intrinsic motivation: on the moderating role of positive and negative emotion differentiation. *PloS one* 9, 12 (2014), e115396.
93. Georgios N Yannakakis, Pieter Spronck, Daniele Loiacono, and Elisabeth André. 2013. Player modeling. In *Dagstuhl Follow-Ups*, Vol. 6. Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik.
94. Georgios N Yannakakis and Julian Togelius. 2011. Experience-driven procedural content generation. *IEEE Transactions on Affective Computing* 2, 3 (2011), 147–161.
95. Georgios N. Yannakakis and Julian Togelius. 2017. *Artificial Intelligence and Games*. Springer. `http://gameaibook.org`.
96. Nick Yee. 2006. Motivations for play in online games. *CyberPsychology & behavior* 9, 6 (2006), 772–775.
97. Alexander Zook, Brent Harrison, and Mark O Riedl. 2015. Monte-carlo tree search for simulation-based strategy analysis. In *Proceedings of the 10th Conference on the Foundations of Digital Games*.

Table 2. Summary of review results

Intrinsic motivation	Implementations in AI	Player modeling and games
Competence	• Empowerment [75, 59, 22]: maximizing the effect the agent can have on its observations through its actions • Sukhbaatar et al. [89] goal generative adversarial network for defining skill-challenge balanced goals for agents • Need for competence in PSI architecture [5]	• Merrick [51] computational model of competence in NPC agents • Merrick and Shafi [55] achievement model • Guckelsberger et al. [24] computational model of empowerment in evaluating game levels • Halim et al. [27] estimation of learnability • Mariusdottir et al. [50] meta-controller for selecting tasks with a level of complexity matching the agent's skill • Cai et al. [14] computational model of competence based on the number of successful and failed actions of an agent • Anthony, Polani and Nehaniv [3] empowerment as intrinsic drive for general game-playing agents
Autonomy	• Empowerment [75, 59, 22]: quantifying the availability of actions in different game states	• Guckelsberger et al. [24] computational model of empowerment in evaluating game levels • Merrick and Shafi [55] power motivation • Anthony, Polani and Nehaniv [3] empowerment as intrinsic drive for general game-playing agents
Curiosity	• Novelty [62, 8, 87]: estimating the visit frequency of states • Surprise [34, 66, 2]: calculating the deviation between observations and predictions • Need for certainty of knowledge in PSI architecture [5]	• Merrick and Maher [53] computational model of curiosity • Park and Kim [65] use curiosity to build an influence map for augmenting a Monte Carlo Tree Search agent • Guerrero-Romero [25] add curiosity heuristics to general video game playing agents • In addition many intrinsically motivated AI papers with curiosity implementations use games such as Montezuma's Revenge as benchmarks; curiosity helps with sparse game rewards. • Cai et al. [14] computational model of certainty based on how recently an object has been visited by the agent
Relatedness	• Loneliness [76] • Social affiliation [5, 18]	• Merrick and Shafi [55] affiliation model • Guckelsberger et al. [23] companion NPC agent that maximizes coupled empowerment • Cai et al. [14] computational model of affiliation based on the number of agent's close friends in a game environment