# Data-Driven Approaches to Game Player Modeling: A Systematic Literature Review

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Modeling and predicting player behavior is of the utmost importance in developing games. Experience has proven that, while theory-driven approaches are able to comprehend and justify a model's choices, such models frequently fail to encompass necessary features because of a lack of insight of the model builders. In contrast, data-driven approaches rely much less on expertise, and thus offer certain potential advantages. Hence, this study conducts a systematic review of the extant research on data-driven approaches to game player modeling. To this end, we have assessed experimental studies of such approaches over a nine-year period, from 2008 to 2016; this survey yielded 46 research studies of significance. We found that these studies pertained to three main areas of focus concerning the uses of data-driven approaches in game player modeling. One research area involved the objectives of data-driven approaches in game player modeling: behavior modeling and goal recognition. Another concerned methods: classification, clustering, regression, and evolutionary algorithm. The third was comprised of the current challenges and promising research directions for data-driven approaches in game player modeling.

CCS Concepts: • **Information systems → Massively multiplayer online games**; *Data mining*; • **Computing methodologies → Machine learning**; *Artificial intelligence*; • **Applied computing → Computer games**;

Additional Key Words and Phrases: Game player modeling, data-driven approaches, computational models, systematic literature review (SLR)

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## 1 INTRODUCTION

Player modeling entails describing a game player's traits and tendencies within a model. Such characteristics may include a player's actions and behavior, dispositions and style, motivations, and aims (Bakkes et al. 2012; Yannakakis et al. 2013). These models can allow a game to tailor its content or goals automatically to suit the needs of a specific player. Adaptation does not necessarily require modeling, since games can respond merely to alterations in the world of play, or to a player's biometric data (Cowley et al. 2016). Nevertheless, there are multiple advantages to developing a

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player model to mediate these responses. First, a player model offers comprehension of a player's behavior, and thus can justify certain adaptations. Second, it makes adaptations generalizable to other games.

There are three domains of data conducive to the building of player models. First among these is gameplay data, that is, data collected immediately from interactions between player and game within the game world. Second is subjective data—that is, data collected via questionnaires (involving, for instance, demographics, emotional states, personality tests, or psychometrics). Objective data constitute a third domain, culled from biometrical observations. There are two basic approaches that are employed in building player models, one theory-driven and one data-driven. A theory-driven approach relies on the social sciences, particularly experimental psychology; it entails advancing a model derived from literature and domain experience, then subsequently using empirical methods to validate the model (Lucas et al. 2013). A data-driven approach, in contrast, relies on the natural sciences and computer science; it first gathers a significant quantity of measurements before applying computational methods to derive models, either fully or semi-automatically (Yannakakis et al. 2013).

Experience has proven that, while theory-driven approaches are able to comprehend and justify a model's choices, such models are frequently missing relevant features because their architects lack sufficient insight. Games, as inherently open-ended constructs, tend to create a massive space of actions. For this reason, data-driven approaches show promise because they do not rely on expert domain knowledge. In addition to being less dependent on expert guidance, data-driven approaches can likewise collect huge quantities of low-level user actions prior to any modular description of those actions (Min et al. 2014). Furthermore, this allows for the granular examination of game player behavior, leading to further understanding. Player movement errors can be examined, for instance, in order to gain insight into the misconceptions that caused them. Such knowledge can then generate more sophisticated cognitive models and a more comprehensive understanding of user behavior.

For these reasons, we are convinced of the promise of data-driven approaches to game player modeling, a belief shared by a number of works (Cowley et al. 2009; Galway et al. 2008; Lee et al. 2014; Machado et al. 2011; Yannakakis 2012; Zook et al. 2012). However, the increasing interest in this field has yet to lead to any effort to link its concepts and techniques. Such an organization of knowledge is vitally important, and requires a systematic review of the current empirical evidence regarding the benefits, challenges, and application of data-driven approaches to game player modeling. To our knowledge, to date there has been neither such a review nor even a summary of empirical evidence. In executing a systematic review of the empirical evidence, this article aims to make several contributions. First, it seeks to offer a review, both systematic and comprehensive, detailing how data-driven approaches have been implemented in game player modeling. Second, it intends to provide a classification of the assorted data-driven approaches to game player modeling. In so doing, it will (third) offer an understanding of the current challenges and promising future directions in the field.

The structure of the article is as follows: Section 2 details the methodology of our review; Section 3 outlines the results and analyzes important studies; Section 4 elaborates on the discussion and considers future directions, limitations, and conclusions.

## 2 RESEARCH METHOD

A systematic literature review (SLR) necessitates a comprehensive and impartial search plan, so as to ensure the completeness of the search of materials under consideration. The recent upswing in interest in the field of data-driven approaches to game player modeling has yet to produce any such comprehensive effort to survey its concepts, methods, and problems; our aim here is to employ Keele's methodology in a much-needed SLR (Keele 2007).

### 2.1 Research Questions

In this SLR, our primary research question is as follows: "What is the state-of-the-art in applying data-driven approaches in game player modeling?" We break this overarching question into three subordinate questions: the first two we address in the results section, because they are empirical in nature, and save the third (more speculative) question for the discussion section.

— RQ1: Considering the surveyed research on data-driven approaches to game player modeling, what basic objectives and methods do the researchers employ?
— RQ2: What are the challenges of using data-driven approaches in game player modeling?
— RQ3: Looking forward, what are promising future directions in data-driven game player modeling?

### 2.2 Database and Keywords

We classified five databases in our search: Springer Link, Science Direct, DBLP, IEEE Xplore, and ACM Digital Library. Additionally, we searched sources outside those databases, in particular scanning bibliographies of relevant articles. However, we did not include Google Scholar among these sources, on account of both the poor precision of its results and the extent to which it overlapped with other data sources. In order to capture the entirety of extant research in this area, we employed a grouping of various keywords. The following search terms were used together *("data-driven approaches" OR "player modeling" OR "data mining" OR "learning individual behavior" OR "user modeling") AND ("game").*

### 2.3 Search Procedure

We display in Figure 1 the three stages of study selection we employed in our systematic review. Throughout these stages, we held meetings to arrive at a consensus concerning any disagreements that arose amongst the reviewers during the selection, assessment, or data extraction processes. We sought thereby to reduce bias to a minimum, and likewise to boost confidence in the study selection process.

As Table 1 shows, we employed criteria of inclusion upon the entirety of the studies gathered in the multiple phases of selection; in doing so, we sought to mine the electronic databases for studies potentially pertinent to the research questions of our SLR. In order to limit the sample to current studies, we established 2008 and 2016 as temporal parameters for the search. There was, in point of fact, a significant quantity of research concerning the use of data-driven methods in game player modeling that predated 2008. We settled on that cutoff, however, because it marks a turning point in the expansion of the interest in, and publications about, the use of data-driven approaches in games. It was immediately followed by the inauguration and development of a number of influential yearly meetings: the IEEE Conference on Computational Intelligence and Games (CIG), the AAAI Artificial Intelligence, and Interactive Digital Entertainment (AIIDE) conference series. For publications that fell within the temporal parameters for our literature search, all titles were screened separately by three reviewers in order to remove publications that obviously fell outside the interests of the current study (such as those concerning approaches to game-based learning and gamification). The next round of evaluation focused on abstracts: the three reviewers examined the abstracts of 238 articles to determine their eligibility, removing all but 94 of them. In the case of any uncertainty concerning a study's relevance based on its title or abstract, we chose to include the study in our full-text evaluation.

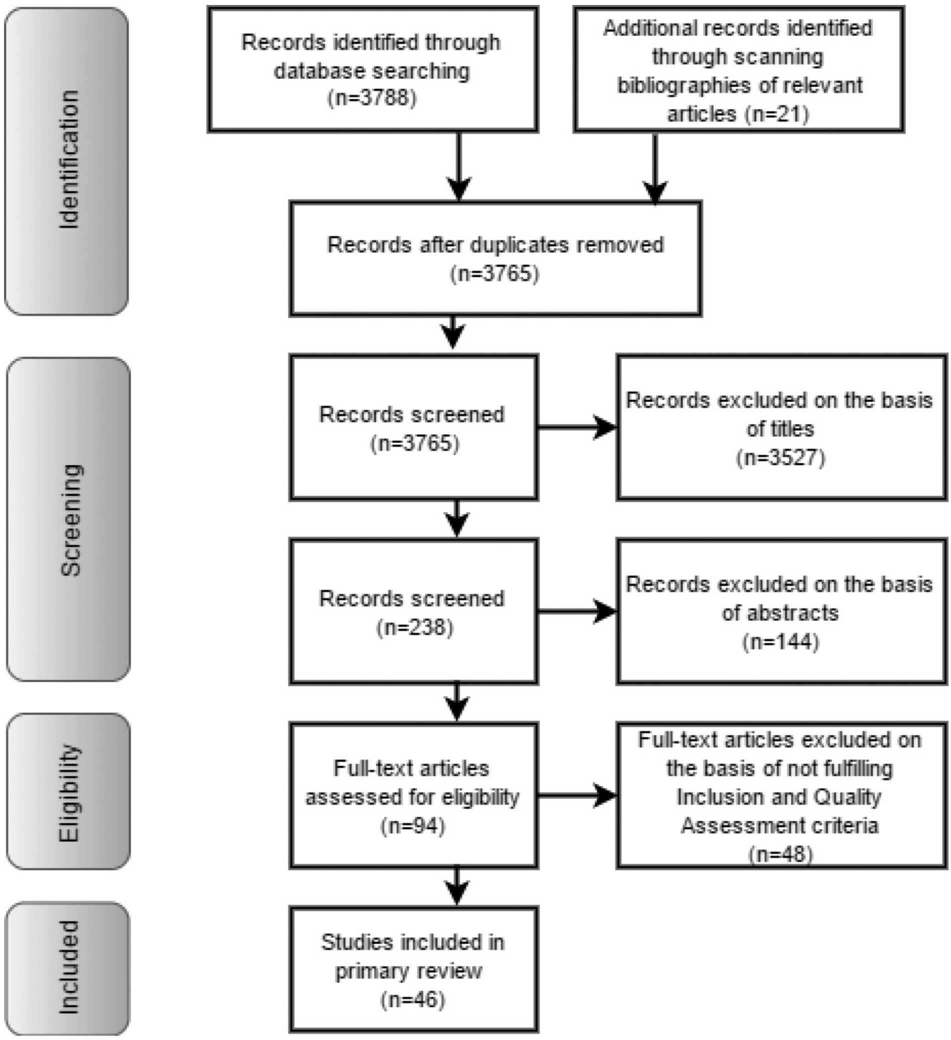


Fig. 1. Study selection procedure.

Table 1. Selection Criteria for Inclusion of Papers

| Inclusion criteria | |
|---|---|
| IC1 | Peer-reviewed articles published in journals or full-length articles published in International Conference/Workshop Proceedings |
| IC2 | Presenting full results |
| IC3 | Dated between 2008 and 2016 |
| IC4 | English language studies |

Third, the full texts of these 94 articles were screened for final eligibility, with matters of inclusion weighed according to the inclusion criteria and quality attributes of Table 2. The 94 articles were distributed to the three reviewers, who carefully reviewed each one in an effort to correct for any bias. The researchers applied the four criteria to assess quality of the articles that had

Table 2. Quality Appraisal Criteria for SLR

| Quality appraisal criteria | |
|---|---|
| QC1 | Frequency of citations |
| QC2 | Methodological contributions |
| QC3 | Sound methodology: Clearly stated goals, limitations, and contributions with transparent and explained experimentation |
| QC4 | Sufficient presentation of the findings |

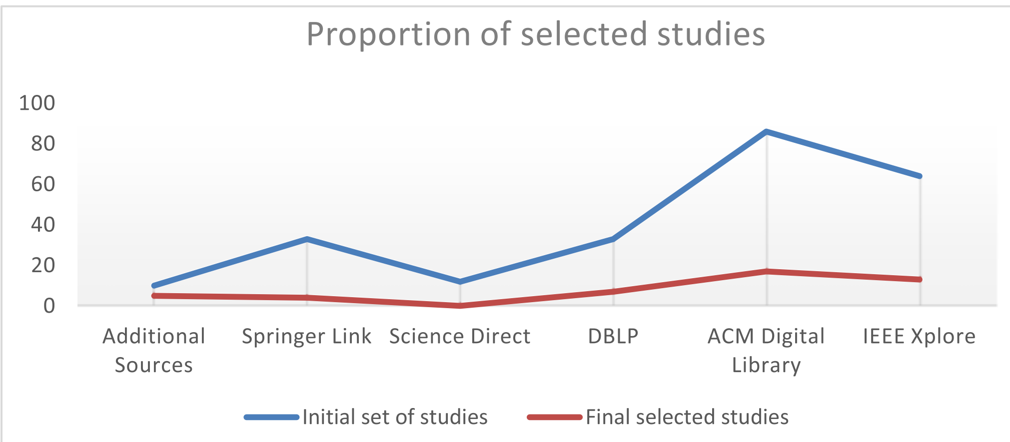


Fig. 2. Ratio of selected studies.

been filtered through the second phase. They used a scale of 1 to 5 (with 5 denoting "very high," 4 "high," 3 "medium," 2 "low," and 1 "very low" on the given category); total scores thus could span from 20 (highest quality, without much risk of bias) to 4 (poor quality, potentially significant bias). Any conflicting opinions arising between the reviewers in the process of selection, assessment, and data extraction were addressed in meetings to reach a consensus. The result of this exhaustive screening process was to winnow the 94 full-text research articles down to 46 research studies of the application of data-driven approaches to game player modeling that were conducted from 2008 to 2016. Thus, the suitability of the articles finally selected for inclusion was assured. Figure 2 presents the number of articles initially derived from each source in proportion to the articles included in the final tally.

The reviewers carefully evaluated the full text of all the studies that passed the second phase, and then catalogued relevant material using a pre-established form for the extraction of data according to research strategy used (Keele 2007). The form included *research discipline, data gathering, research objectives, data acquisition, analysis technique*, and *results*. The demographics and overview of these studies are presented in Appendix A.

## 3 RESULTS AND KEY STUDIES ANALYSIS

### 3.1 Research Discipline

While specific topics vary according to study, the majority address three primary areas: behavior/experience modeling, goal/plan recognition, and procedural content generation. This list of areas of potential is by no means comprehensive, but it represents a major slice of research and development at present.

## 3.2 Data Gathering

The reviewed research studies gathered data from different data sources (games). More details, including game purposes, are given in Table 3. In total, 32 concerned entertainment and 14 addressed learning-focused games. While entertainment and learning frequently overlap (since many games aim at both), we divided them along these lines to distinguish specifically pedagogical games from the rest.

## 3.3 Research Question 1

**RQ1:** Considering the surveyed research on data-driven approaches to game player modeling, what basic objectives and methods do the researchers employ?

In our examination of the reviewed works, we found that most studies share a basic set of objectives: player behavior modeling/experience modeling, goal/plan recognition, and procedural content generation. Authors have used a range of Artificial Intelligence (AI) methods to pursue some specific tasks. This section presents the fundamental objectives, approaches employed, and their application in some works. Table 4 classifies and presents the selected studies according to research objectives. We characterized as "behavioral modeling" methods of player behavior modeling, experience modeling, and procedural content generation present in the reviewed studies, because they frequently necessitate a functional model of the player and/or his behavior. Even though player modeling significantly overlaps with goal/plan recognition, as such recognition entails a problem in which action sequences are interpreted in terms of the goal they are most probably attempting to realize, we decoupled behavior modeling from plan/goal recognition because it sidesteps the process of predicting goals and deducing behavior from them and instead predicts behavior directly. In the pool of studies under review, 34 address player behavior modeling, while 12 address goal recognition. As this distribution clearly demonstrates, the field has been tilted towards player behavior modeling, such that this area dominates the spotlight with regards to current research and advances.

Our review also considered another vital parameter: namely, the method of data analysis which researchers apply to their collected data (see Table 5). As Table 5 clearly shows, classification is strongly favored in player modeling, whereas clustering and regression are employed in a more limited fashion. The area of player modeling appears moreover to contain a particularly varied and rich array of AI methods. In order to delineate the classification of methods presented here, it should be understood that supervised learning indicates learning a model in which instances of datasets are aligned with target values (such as classes); target values are thus a prerequisite for supervised learning (as in neural networks). In contrast, unsupervised learning describes algorithms that locate patterns in datasets without target values (e.g., k-means). Evolutionary computation indicates population-based global stochastic optimization algorithms, such as genetic algorithms. One might of course categorize these methods in a different manner, but our contention is that the classification we put forward is succinct and adheres to typical method classifications in artificial and computational intelligence.

### *3.3.1 Behavior Modeling.*

As Table 4 shows, one of the main objectives of the reviewed research studies is to detect, identify, and model the behavior of players, as behavior modeling constitutes the research objective of 34 studies.

In particular, these studies aim to model the behavior and experience of game players, and from that to design-predictive models of user behavior and movement to generate game contents (see A1-A5, A7, A12, A14-A23, A27-A29, A31, A33-A40, and A42-A46 in Appendix A). Several AI techniques have been studied and used for modeling player behavior by the authors of reviewed research studies, such as classification, clustering, regression and evolutionary algorithms. We

Table 3. Games Used in the Reviewed Research Studies

| Paper ID in Appendix A | Game | Purpose | Reference |
|---|---|---|---|
| A1 | Alice in AreaLand | learning | (Falakmasir et al. 2016) |
| A2 | Combat with Monsters | learning | (Zook et al. 2012) |
| A3 | The Hunter | entertainment | (Ramirez-Cano et al. 2010) |
| A4 | Forza Motorsport 5 | entertainment | (Harpstead et al. 2015) |
| A5 | World of Warcraft | entertainment | (Harrison and Roberts 2011) |
| A6, A13,A24,A25, A41 | CRYSTAL ISLAND: OUTBREAK/ CRYSTAL ISLAND: UNCHARTED DISCOVERY | learning | (Baikadi et al. 2011; Ha et al. 2012; Min et al. 2016a, 2016b, 2014) |
| A7, A17 | Infinite Mario | entertainment | (Shaker et al. 2010; Weber et al. 2011) |
| A8,A26,A30, A32 | StarCraft | entertainment | (Bisson et al. 2015; Kabanza et al. 2010; Synnaeve and Bessiere 2011; Weber and Mateas 2009) |
| A9 | The Legend of Zelda | entertainment | (Gold 2010) |
| A10 | Rush Football | entertainment | (Laviers and Sukthankar 2011) |
| | | | |
| A11 | The Restaurant Game | entertainment | (Orkin et al. 2010) |
| A12,A29 | Tomb Raider: Underworld | entertainment | (Drachen et al. 2009; Mahlmann et al. 2010) |
| A14,A38 | Pac-Man | entertainment | (Cowley et al. 2009; 2013) |
| A15 | Anchorhead | entertainment | (Sharma et al. 2010) |
| A16 | Blindmaze | entertainment | (Etheredge et al. 2013) |
| A18 | Civilization IV | entertainment | (Spronck and den Teuling 2010) |
| A19 | Cannon & spaceship | entertainment | (Missura and Gärtner 2009) |
| A20 | Bug Smasher | entertainment | (Yannakakis and Hallam 2009) |
| A21 | DragonBox | learning | (Lee et al. 2014) |
| A22,A42 | REFRACTION | learning | (Butler et al. 2015; Liu et al. 2013) |
| A23 | Choose-Your-Own-Adventure | entertainment | (Yu and Riedl 2012) |
| A27 | Sony Everquest II | entertainment | (Borbora and Srivastava 2012) |
| A28 | Super Mario Bros | entertainment | (Pedersen et al. 2010) |
| A31 | Madden NFL 11 | entertainment | (Weber et al. 2011) |
| A33 | Snakeotron | entertainment | (Gow et al. 2012) |
| A34 | Food Distribution | learning | (Luo et al. 2016) |
| A35 | Space Invaders | entertainment | (Anagnostou and Maragoudakis 2009) |
| A36 | Destiny | entertainment | (Tamassia et al. 2016) |
| A37 | I Am Playr/Lyroke | entertainment | (Xie et al. 2014) |
| A39 | SeaGame | learning | (Bellotti et al. 2009) |
| A40 | Solving the Incognitum | learning | (Valls-Vargas et al. 2015) |
| A43 | Resource Management Game | learning | (Grappiolo et al. 2011) |
| A44 | Battle with monsters | entertainment | (Zook and Riedl 2012) |
| A45 | SUPER MONKEY BALL 2 | entertainment | (Cowley et al. 2014) |
| A46 | Table tennis game | entertainment | (Gao et al. 2016) |

Table 4. Research Objectives of the Reviewed Studies

| Research objectives (goals) | Number of papers | Reference |
|---|---|---|
| Player behavior modeling/ Experience modeling/Procedural content generation | 34 | (Anagnostou and Maragoudakis 2009; Bellotti et al. 2009; Borbora and Srivastava 2012, Butler et al. 2015; Cowley et al. 2009, 2013, 2014; Drachen et al. 2009; Etheredge et al. 2013; Falakmasir et al. 2016; Gao et al. 2016; Gow et al. 2012; Grappiolo et al. 2011; Harpstead et al. 2015; Harrison and Roberts 2011; Lee et al. 2014; Liu et al. 2013; Luo et al. 2016; Mahlmann et al. 2010; Missura and Gärtner 2009; Pedersen et al. 2010, Ramirez-Cano et al. 2010; Shaker et al. 2010; Sharma et al. 2010; Spronck and den Teuling 2010; Tamassia et al. 2016; Valls-Vargas et al. 2015; Weber et al. 2011a, 2011b; Xie et al. 2014; Yannakakis and Hallam 2009; Yu and Riedl 2012; Zook et al. 2012; Zook and Riedl 2012) |
| Goal/plan recognition | 12 | (Baikadi et al. 2011; Bisson et al. 2015; Gold 2010; Ha et al. 2012; Kabanza et al. 2010; Laviers and Sukthankar 2011; Min et al. 2014, 2016a, 2016b, 2014; Orkin et al. 2010; Synnaeve and Bessiere 2011; Weber and Mateas 2009) |

characterize the AI methods that are primary or secondary in each approach. Primary methods denote the techniques most frequently applied in the literature, whereas secondary methods denote ones that appear in a significant number (but not a majority) of studies.

In reviewing the studies given in Table 5, we discovered that a number of classification algorithms are employed in the behavioral modeling of game players. These include Hidden Markov Models (HMM), Bayesian Networks (BN), Markov Logic Networks (MLN), Support Vector Machines (SVM), Neural Networks (NN), Long Short-Term Memory (LSTM), Recursive Neural Networks (RNN), K-Nearest Neighbor (KNN), Decision Trees (DT), and Deep Learning (DL). The classification algorithms employed most often for behavior modeling were the NN and its variant, as well as MLN and HMM, which thus garnered increased attention concerning their modeling potential (see A16, A17, A20-A22, A28, A34, A36 and A43 in Appendix A). After these, the next in popularity were SVM and DT (A19, A37, A38 and A40). Note that classification methods were sometimes paired with clustering or evolutionary algorithms in the studies under review; in such

Table 5. Data Analysis Method of the Reviewed Studies

| Data analysis method | Algorithm | Category | Number of papers | Reference |
|---|---|---|---|---|
| Classification | Hidden Markov Models, Bayesian Network, Markov Logic Networks, Input-Output Hidden Markov Model, Decision Tree, Support Vector Machine, Neural Network, Recursive Neural networks, Long Short-Term Memory Network, Deep learning, K-Nearest Neighbor | Supervised Learning | 31 | (Baikadi et al. 2011; Bisson et al. 2015; Butler et al. 2015; Cowley et al. 2009; Cowley et al. 2013; Etheredge et al. 2013; Gold 2010; Grappiolo et al. 2011; Ha et al. 2012; Harrison and Roberts 2011; Kabanza et al. 2010; Laviers and Sukthankar 2011; Lee et al. 2014; Liu et al. 2013; Luo et al. 2016; Mahlmann et al. 2010; Min et al. 2014; 2016a; 2016b; Missura and Gärtner 2009; Orkin et al. 2010; Pedersen et al. 2010; Shaker et al. 2010; Spronck and den Teuling 2010; Synnaeve and Bessiere 2011; Tamassia et al. 2016; Valls-Vargas et al. 2015; Xie et al. 2014; Yannakakis and Hallam 2009; Yu and Riedl 2012; Zook and Riedl 2012) |
| Clustering | k-means, CURE (Clustering Using REpresentatives), SOM (Self-Organizing Map), Spectral clustering, LDA (Linear Discriminant Analysis) | Unsupervised Learning | 7 | (Anagnostou and Maragoudakis 2009; Borbora and Srivastava 2012; Cowley et al. 2014; Drachen et al. 2009; Gow et al.2012; Ramirez-Cano et al. 2010; Sharma et al. 2010) |
| Regression | Linear regression, Regression trees, Additive regression, Logistic regression | Supervised Learning | 6 | (Falakmasir et al. 2016; Gao et al. 2016; Harpstead et al. 2015; Weber and Mateas 2009; Weber et al. 2011a, 2011b) |
| Evolutionary Algorithms | Genetic algorithm | Evolutionary computation | 2 | (Bellotti et al. 2009; Zook et al. 2012) |

cases, we labeled them under classification, since the data-driven methods those articles advanced depend primarily on the methods of classification.

Liu et al. (2013), for instance, worked out a method to predict player behavior and movement in an educational game. Their algorithm selects from a combination of methods—Markov models, state aggregation, and player heuristic search—according to whichever offers the largest amount of data. Their approach promises to minimize the burden of hand-designing a cognitive model and system-specific features. Lee et al. (2014) likewise developed a framework for predicting player movements within a pair of puzzle games, which, they showed, greatly outperformed both games' baselines. They proposed a data-driven approach, a mixture of a one-depth heuristic search model and a data-driven Markov model with no knowledge of individual history other than the current game state, to learning individual behavior. They added to the prior framework by constructing a state-action graph and employing methods of feature selection to minimize the number of features for each state. They then applied this new framework to another game (DragonBox) to ascertain its applicability for extension, and reported similar success. The studies undertaken by Lee et al. (2014) and Liu et al. (2013) hold the potential to address the two main issues of purely data-driven approaches—their failure to offer any semantically meaningful interpretation of outputs, on the one hand, and their shortcomings in algorithmic efficiency on the other. However, unlike the method proposed by Lee et al. (2014), Liu et al. (2013) assume that players do not change over time and define a user reward as a combination of pre-defined heuristics. Thus, the quality of the learned policy is strongly dependent on these heuristics, which are often system-specific and time consuming to refine. Lee et al. (2014) overcome this issue by incorporating temporal variations in player performance, thus allowing for modeling change in a player's skill over time.

Pedersen et al. (2010) took a different tack, developing a neural network which charts three elements—behavioral characteristics of players, their self-reported emotions, and level parameters—in order to be able to successfully predict from in-game behavior and content what sort of affective experiences (enjoyment, frustration, effort, etc.) the players might report. This approach begins by studying play style, then constructs a model of users' preferences from which it produces levels to meet those desires. In so doing, they assume that a user's preferences remain fixed within a game session. However, if this assumption is suspect (or if a player's style of play might undergo variation), then a more adaptable model is needed to observe and describe how a player's behavior changes over time. Valls-Vargas et al. (2015) addressed this issue in proposing a new framework for player modeling, one which does not depend on the notion of fixed player style but instead attempts to predict a dynamic state of play. This framework captures fluctuations in player behavior through the use of episodic information and time interval models within a sequential machine learning method capable of learning several models progressively (such as a Support Vector Machine or Decision Tree). Testing various strategies of trace segmentation for predicting player style, they found that sequential machine learning approaches are superior to non-sequential ones when they include predictions from prior segments. Moreover, they found that predictive performance declines when the trace segmentation is either too detailed (minute-by-minute) or too imprecise (entire traces).

Factor analysis is also frequently employed in learning individual behavior. Zook and Riedl (2012) developed a tensor factorization technique for anticipating a player's performance in skill-based computer games. This data-driven tensor factorization method offers more precise adaptations of challenges to individual players because it is capable of forecasting alterations in a player's game mastery in time. They show via an empirical study (involving game users engaging a basic role-playing combat game) that tensor factorization models are both effective and easily scalable. But while their approach can even incorporate temporal behavior by including time factors, such approaches do not easily fit games which require predicting a fine granularity of action instead of predicting user's single valued performance.

After classification algorithms, various regression techniques coupled with clustering algorithms have been used in a pair of studies (see A1, A3, A4, A7, A12, A15, A27, A30, A31, A33, A35, A45, and A46 in Appendix A). These approaches primarily use clustering to obtain appropriate groupings of players and then perform a regression method within each group. Hence, we find the primary and secondary methods of player behavior modeling to be classification first, regression algorithms generally coupled with clustering techniques second.

Mahlmann et al. (2010), for example, considered whether one can forecast specific aspects of player behavior, examining by way of supervised learning the commercial game *Tomb Raider: Underworld* (TRU). Specifically, they sought to anticipate the moment at which a player will cease playing, or conversely how long the player would take to finish a game. The manufactured predictors focus on metrical data derived from game play in the two initial levels of TRU. The outcomes clearly demonstrate the efficacy of linear regression techniques as well as nonlinear approaches to classification.

Mere evolutionary algorithms were the least commonly applied data-driven approach for learning player behavior (see A2 and A39 in Appendix A). For instance, Bellotti et al. (2009) devised an engine for learning games derived from evolutionary computation approaches such as genetic algorithm and reinforcement learning (which separate expertise in game design from domain expertise). Their method approaches the design of a learning game in terms of task authoring: domain experts identify and gloss domain knowledge to manifest within gameplay as tasks and task selection, while game designers establish the manner in which tasks are represented and chosen. A game experience module would then, at the start of a game, determine from a player's profile what subset of tasks to generate. In this manner, the game experience module takes on a double role: it becomes at once a domain expert (ascertaining a player's current capabilities and knowledge level) and a designer (selecting and staging suitable game tasks).

*3.3.2 Goal Recognition.* Abductive reasoning seeks to discern the user's intentions by studying his or her actions (Carberry 2001). This is referred to as goal recognition, and it views the user as enacting goal-directed behavior (or, broadly speaking, understands that he/she is aiming at realizing a specific state in the world). What goal recognition seeks to accomplish is to derive, from a user's prior actions and knowledge of the domain, an understanding of the state that the user seeks to realize in the world. Goal recognition is closely related to the challenges involved in other forms of recognition—specifically, of actions and plans. The former, also known as activity recognition (Turaga et al. 2008), deduces a user's action from sensory information (for instance, computer vision); whereas plan recognition (Kautz 1987) tackles the broader, more difficult challenge of predicting both a user's goal and the precise sequence of actions by which he or she will pursue it. In method, goal recognition can be categorized into alternate approaches—one rooted in planning systems, another rooted in models of probability. Each type of goal recognition possesses its own technological limitations, but that is a topic beyond the focus of this study.

Notably, player modeling significantly overlaps with goal/plan recognition, as such recognition entails a problem in which action sequences are interpreted in terms of the goal they are most probably attempting to realize. Plan recognition algorithms capture a set of observations and from it generates a set of goals that can account for the observed content. The smallest set of goals that can account for a sequence of actions is generally deemed superior to larger sets, since it probably holds more significant explanatory value (Carberry 2001). These methods of plan recognition are also applicable to forecasting player behavior: if a player's goal can be ascertained, it follows that the player will execute the intervening steps necessary for completing those goals. Player modeling differs from plan recognition, however, in that it sidesteps the process of predicting goals and deducing behavior from them and instead predicts behavior immediately.

Table 4 demonstrates the importance of goal recognition in player modeling, as goal recognition constitutes the research objective of 12 studies. In these articles, the authors pursue the prediction or recognition of goals, plans, and actions (see A6, A8-A11, A13, A24-A26, A30, A32, and A41 in Appendix A). Several AI techniques have been studied and used for predicting goals, plans, and actions by the authors of reviewed research studies (see Table 5), such as classification, clustering, regression, and evolutionary algorithms. For each approach, as with behavior modeling, we have determined the primary or secondary AI techniques employed. In reviewing the studies given in Table 5, we discovered that a number of classification algorithms are used in goal/plan recognition. These include HMM, MLN, SVM, BN, LSTM, RNN, and DL. The classification algorithms employed most often for goal recognition were the MLN, HMM, and NN and its variant, which thus garnered increased attention concerning their modeling potential (see A6, A9, A13, A25, A26, and A41 in Appendix A). After these, the next in popularity were SVM (A10), BN (A32), and DL (A24). After classification algorithms, regression techniques along with clustering algorithms have also been used in a pair of studies (see A8 and A30 in Appendix A). Evolutionary algorithms, however, were not applied for goal recognition.

Ha et al. (2011), for instance, apply MLNs to develop a successful goal recognition framework for players. This framework employs model parameters derived from a corpus of player interactions within a nonlinear game and enables an automatic goal recognition system superior to a number of baseline models. MLNs are also put to work in a similar goal recognition approach, by Baikadi et al. (2011), wherein problem-solving goals are linked to discovery events by means of probabilistic inference and first-order logical reasoning. When empirically tested, models employing discovery events-based models surpassed previous best approaches on all fronts. However, in using this approach—a combination of hand-authored logic formulae and machine-learned weights—some labor-intensive feature engineering efforts need to be eliminated (by utilizing, for example, multi-level feature abstraction techniques).

Another method is put forward in a study by Gold (2010), in which an Input-Output Hidden Markov Model (IOHMM) is trained to identify a player's goal within an action-adventure game. The goals—the hidden states in the IOHMM—were Fight, Explore, and Return to Town, and the observation model learned through players being directed toward specific goals and counting actions. Initially, there was little difference in performance between models trained to specific first-time players and the model trained to the experimenter. Subsequent models trained to these same players' ensuing gameplay vastly improved, however, over both the first-time player- and the experimenter-trained models. In other words, it appears that game goal recognition systems work best with players who have developed a specific playing style. It should be noted that the proposed approach by Gold (2010) was compared to a hand-authored finite state machine, a common computational framework used in commercial games, where the results showcase the effectiveness of the proposed approach; computational approaches based on deep learning for goal recognition, however, outperform the proposed approach (Min et al. 2014).

Furthermore, Min et al. (2014) developed a goal recognition framework grounded in stacked denoising autoencoders (a form of deep learning), in which the goal recognition models are trained through a corpus of player interactions. These models featured superior performance—significantly outperforming the best of the MLN-based goal recognition frameworks—and, moreover, present a profound advantage in that they require no labor-intensive engineering of features.

Laviers and Sukthankar (2011) have developed a technique for the real-time adaptation of plan repair policies, by means of Upper Confidence Bounds applied to Trees (UCT). Their research shows how such policies can, in a game of American football, be paired with plan recognition to generate a fully autonomous offense that can counter surprising shifts in defensive strategy. The offense produced by this real-time UCT approach easily surpassed both the baseline game and domain-specific heuristics in offensive efficiency, measured in average yardage and turnover avoidance. They cannot model goal alterations, however—that is, instances wherein a player adopts a new goal and forsakes the previous one. Moreover, this approach is unable to speak towards the relative superiority of training individual players versus aggregating player behavior, or the question of whether the usefulness of models depend on players having in-game experience.

Alternate approaches involve employing LSTM to learn these frameworks—goal recognition, multiple-goal recognition, task recognition, and plan repair policies. Regarding the use of latter in adversarial games, it is advisable to pair it with plan repair, for the reason that such games frequently require players to undertake a plan prior to being able to gauge the intentions of the opponent. This is especially true of multi-agent domains, in which it is not computationally possible to undertake total replanning. Hence, Min et al. (2016b) have approached goal recognition as a sequence labeling task by means of LSTM. Such an approach to goal recognition outperforms previous techniques (e.g., Markov's logic network-based models and n-gram encoded feed forward neural networks pre-trained with stacked denoising autoencoders) in accuracy testing. In this respect, LSTM-based approaches apparently solve a major problem in game player modeling, at once offering superior accuracy in goal recognition and also eliminating the exhaustive engineering previously required for such modeling.

### 3.4 Research Question 2

**RQ2:** What are the challenges of using data-driven approaches in game player modeling?

We present an overview in this section of major challenges to developing data-driven methods in game player modeling. In scrutinizing the reviewed works, we came to understand that data-driven approaches, while promising exciting advancements in game player modeling, present researchers with various challenges (see A1-A6, A12-A15, A18-A22, A24, A25, A27-A30, A33, A34, A36, A38, A39, A44, and A45 in Appendix A). These include:

— *Insufficient or Inaccessible Data:* Regardless of their specific area of focus in game player modeling, researchers struggle first and foremost with a dearth of publicly available, robust data. An expansive multimodal body of data and descriptions of gameplay and players is particularly urgent. Such a body of data must exhaustively cover gameplay data for a few highly populated multiplayer games—their actions and locations, events and timestamps. Moreover, researchers must be able to draw on information concerning players' demographics, questionnaire responses, and formal interviews (Of course, such data need not extend to every player in the database). The database should also incorporate the few significant databases of gameplay available at the present.

— *Heterogeneous Data:* While some machine learning methods, such as logistic regression, and ad hoc graphical models do promise certain advantages in analyzing and mining particular games data, they demand too much expert adjustment to be more widely applicable. There is also the challenge of interpreting a scarcity of raw data for sophisticated player modeling. This difficulty necessitates a comprehensive data-driven method, one which is not reliant on costly domain knowledge engineering and which produces a coherent and understandable model that is accurate both in its account of the data and in its prediction of game outcomes.

— *Problem of Generalizability:* The problem of generalizability describes a gaming situation in which an agent adapts only to a limited set of states in a game's world and is unable to generalize beyond them. It causes poor performance as soon as the game states change, or the agent engages new states. The standard technique in applied machine learning for preempting the tendency towards generalizability—a set of validation examples—might prove insufficient in a game environment, on account of both the time required to learn a set of validation examples and the difficulty of extracting such a set from a scarcity of training data.

— *Algorithmic Efficiency:* In highly populated and open-ended games, the massive amount of data collected can rapidly overwhelm players' PCs or gaming consoles. The solution to this technical difficulty requires a separation of modeling and predicting into two noncoterminous phases. A model can be developed offline, for instance, unconstrained by any untenable efficiency requirements, leaving only the prediction phase to be executed online with the efficiency necessary to prevent gameplay delays.

— *Data Scarcity Problem:* For a number of reasons, it is difficult to develop a set of training examples for games with a large search space, and particularly for games where a relevant example might be bound up with a series of delayed, interleaving, or compounding results. In such cases, player-generated material might have to provide the training examples, unless concrete targets can be removed from the learning process altogether. This scarcity of data can be offset, though, by joining methods of collaborative filtering with external information offered by content-based approaches.

— *Knowledge Engineering:* Multiple data-driven methods (e.g., Knowledge tracing/Bayesian network models) are unable to connect modeled player types to game events on their own, and must be supplemented by knowledge engineering annotations. Hence, these approaches remain fundamentally reliant on expert authoring, in that expert authoring is necessary for task definition and the system-specific network models that generate the network structures that provide knowledge of users. This state of affairs is not sustainable. Data-driven methods must be constructed so as to cut down the amount of hand designing that goes into cognitive modeling and system-specific features.

— *Temporal Forecasting in Player Models:* Temporal forecasting is a central component of player predictions, since a player's abilities and choices will fluctuate in time, and since such forecasting enables the development of sequential content. For this reason, even though most data-driven methods (e.g., collaborative filtering algorithms) are generally accurate, efficient, sufficient, and predictive, regardless of domain—especially in instances in which scarce data on individual players are offset by data gathered on other players—they must nevertheless factor for temporal performance variations so as to model a player's changing abilities in time.

## 4 DISCUSSIONS

### 4.1 Research Question 3

**RQ3:** Looking forward, what are promising future directions in data-driven game player modeling?

Here we outline four promising future directions in the application of data-driven approaches in game player modeling (see A1, A5, A14, A19-A21, A25, A27-A30, A38, and A39 in Appendix A).

— *Data Mining Techniques for Individual Prediction:* While data-mining techniques have been shown to offer, via careful application, insight regarding the behaviors of groups, their utility in predicting individual behavior is still limited. Hence, player models generally offer only broad and fuzzy indications for ways in which a game should tailor itself to specific players (Yannakakis et al. 2013). One potential solution to this problem is to define a few player models and then categorizes individual players accordingly. In subsequent gameplay, the model can undergo small changes to better match the player. In other words, rather than viewing the model as a fixed representation of the player, by which the game makes adaptation decisions, it is seen as a dynamic representation of a group of players that modulates to match a specific player's characteristics and thus initiates dynamic adaptation in the game. We believe that this second approach to game adaptation via player modeling offers practical advantages: it can quickly produce effective results in developing educational games that offer a personalized form of engagement to the player.

— *Hybrid Player Modeling Approaches:* In analyzing model-free and model-based methods of player modeling, we observe that model-free approaches manifest none of the argumentation and interpretation concerning the model's choices that model-based approaches inevitably involve. And yet, model-based methods frequently overlook relevant features because their builders did not have sufficient insight, whereas model-free methods will automatically detect such features (Yannakakis 2012). The error of model-free approaches, however, is a tendency to deduce connections between user attributes, experience, and context that are entirely meaningless. These points to a broader present issue particularly in open-ended games: such games present the chance to collect and measure a set of player behavior features far more extensive than our current understanding of what these features might signify. Given this situation, model-free methods seem preferable, even though meaningful player models require domain-specific knowledge and the extraction and selection of features. We believe that one must characterize model-based and model-free approaches as points at either end of a continuum, along which one can place various hybrid efforts to understand player behavior in games.

— *Data-Driven Approaches to Conceptualizing Log Data:* While log files generated by games allow the researcher to learn behavior of players as they play the game, there are a number of practical issues associated with analyzing such data. To name a few, log files represent prohibitively large quantities of data; it is hard to interpret them since the responses of individual player are highly context dependent. It is also difficult to determine which actions represent key features of player performance given that log files are generally designed to capture all player actions relevant to game play, and not until after analysis can one know which of those actions were relevant to learning. For this reason, we hold that a data-driven approach offers significant promise to researchers, insofar as it does not depend on expensive domain knowledge engineering, and insofar as it can select and extract the essential conceptual features of player performance from games' log data.

— *Data-Driven Approaches to Modeling Players in Infinitely Open and Replayable Worlds:* Interest has never been higher in the promise procedural content generation methods hold for optimized game design, in both commercial and independent game development. It is now assumed that new games will have more user-generated or procedurally.generated content than manual content, particularly because costly and bottlenecked content creation are major impediments in the game development process. But as automatically generated games become more common, it becomes increasingly difficult to model players in endlessly open worlds of infinite replayability value. Here also we are of the mind that researchers would significantly benefit from a data-driven approach that is not dependent on expensive domain knowledge engineering and can model players within such infinitely open and replayable worlds.

### 4.2 Limitations

We have constrained our references with the criteria of inclusion. Additionally, we have included, in applying assessment criteria, studies that addressed the work that initially generated the specific lines of research discussed. Readers must be advised that it is impossible to exhaustively review, in a single article, the myriad aspects of data-driven methods in game player modeling. In fact, certain topics (such as procedural content generation) are deserving of an entire review on their own. Rather, our aim here has been to give a representative selection of current research within each learning method.

### 4.3 Conclusions

In spite of the increased interest in data-driven approaches to game player modeling, there has yet to be any effort to review current empirical evidence regarding the benefits, challenges, and applications of such approaches. This article has thus focused on conclusions from empirical studies, thereby offering a systematic overview of the evidence pertaining to data-driven approaches in game player modeling. By examining the available literature for representative, rigorous, and frequently cited case studies from game player modeling domains, we cast light on the data-driven approaches that have been employed and in so doing demonstrate the potential held by this new field in game research. In Table 6, we present our findings concerning the aims of data-driven approaches to player modeling in games, the algorithms employed in this type of player modeling, and the present difficulties and future directions of game player modeling.

While previous methods relied on questionnaires to gain insight into perceptions and attitudes, now every movement and "click" in an electronic learning environment might encode useful information that can be tracked and interpreted. Computational methods offer the potential to isolate,

Table 6. Objectives, Techniques, Current Challenges, and Future Directions of Data-Driven Approaches to Game Player Modeling

| |
|---|
| Research Objectives of the Reviewed Empirical Evidence |
| Player behavior modeling (experience modeling/procedural content generation) |
| Goal/plan recognition |
| Data-driven Techniques in Game Player Modeling |
| Classification |
| Clustering |
| Regression |
| Evolutionary Algorithms |
| Current Challenges |
| Insufficient or inaccessible data |
| Heterogeneous data |
| Problem of generalizability |
| Algorithmic efficiency |
| Data scarcity problem |
| Knowledge engineering |
| Temporal forecasting in player models |
| Future Directions |
| Data mining techniques for individual prediction |
| Hybrid player modeling approaches |
| Data-driven approaches to conceptualizing log data |
| Data-driven approaches to modeling players in infinitely open and replayable worlds |

identify, and categorize any simple or complex action within a game, placing it within meaningful patterns. Interactions of all sorts can be coded into behavioral patterns and interpreted to guide decision-making. This exciting juncture lies at the crossroads of computer and learning science, psychology, and pedagogy. What remains is to grasp the deeper learning processes by means of breaking them down into simpler and discrete mechanisms. It is our hope and belief that this active area of research will continue to provide invaluable contributions to the development of dynamic, powerful, and accurate games, both for designers and for players.

## APPENDIX A

Demographic data and overview of the selected studies:

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