AI in (and for) Games

Kostas Karpouzis\textsuperscript{1} and George Tsatiris\textsuperscript{2}

\textsuperscript{1} Panteion University of Social and Political Sciences, Athens, Greece, kkarpo@cs.ntua.gr.
\textsuperscript{2} Artificial Intelligence and Learning Systems Laboratory, National Technical University of Athens, Greece

Abstract. This chapter outlines the relation between artificial intelligence (AI) / machine learning (ML) algorithms and digital games. This relation is two-fold: on one hand, AI/ML researchers can generate large, in-the-wild datasets of human affective activity; player behaviour (i.e. actions within the game world), commercial behaviour, interaction with graphical user interface elements or messaging with other players, while games can utilise intelligent algorithms to automate testing of game levels, generate content, develop intelligent and responsive non-player characters (NPCs) or predict and respond player behaviour across a wide variety of player cultures. In this work, we discuss some of the most common and widely accepted uses of AI/ML in games and how intelligent systems can benefit from those, elaborating on estimating player experience based on expressivity and performance, and on generating proper and interesting content for a language learning game.

Keywords: machine learning, artificial intelligence, games, procedural content generation, affective computing, player behaviour, computational culture

1 Introduction

Digital games have enjoyed a huge wave of popularity among the research community in the past years. An important reason for this is the fact that games combine the characteristics and requirements of performance/narrative media \cite{11} with high-maintenance software and hardware requirements for storage, CPU performance, network communication \cite{51} and security \cite{32}. Especially in the field of computer hardware, digital games have been a driving force for the industry to produce newer, more effective and less power-demanding hardware for PCs and game consoles \cite{45}, pushing their capabilities further and further.

Another important fact that makes digital games extremely popular as a research medium has to do with the relative ease to find participants for games research studies: Pew Research \cite{46} mentions that “43\% of U.S. adults say they often or sometimes play video games on a computer, TV, game console or portable device”, with puzzle and strategy games constituting the most popular genres among those who often or sometimes play video games. As a result, researchers working with games, either in the core of their work or as a means to attract users
and record their behaviour or preferences, can quickly put together large corpora
of data (e.g. [24] or [55] for a database which captures player expressivity asso-
ciated with player behaviour or [18] for a 3D dataset describing tennis-related
actions in video and 3D skeleton form).

Among the research areas that embraced digital games as a platform of
choice, perhaps the most celebrated one has been the combination of Artificial
Intelligence (AI) and Machine Learning (ML), mostly because of the popularity
of AI/ML algorithms which competed against and eventually beat human world
champions in Chess [9] and more complex board games such as Go ([58], [59]).
Games are a fitting medium to train and test AI/ML algorithms because of the
relatively small search space in which to look for and identify the best possible
turn and, mostly, for the completeness and robustness of the definition of the
game world in terms of variables, rules and relations. Conversely, game design
and development has been putting to use AI/ML algorithms to create content
automatically or in a user-guided manner, to estimate and adapt player experi-
ence ([19], [73]) or predict player behaviour [12]. In this chapter, we will start
with identifying possible sources of data to be used to train and test AI/ML
algorithms; in the following, we will discuss the areas of conversation between
intelligent algorithms and digital games, providing examples of identification of
player behaviour and prediction of player experience, and elaborate on game
content generation for serious games in education.

2 Game content and databases

Perhaps the most important component for the interplay between AI/ML, along
with the actual algorithms and their context or use case, is the selection and
role of data or content to be used or generated. In game design and development
terminology, content refers to a wide variety of concepts, data and types of
media within a game world. An interesting distinction is that besides content
being included in the game as part of its design or interactive functionality, it
can be generated by the game during game play [1], usually as a response of
the game world to the choices and actions performed by the player, or it can be
created by the players themselves [26]. The latter case is usually referred to as
“user” (UGC) or “player-generated content” and covers personalisation of the
appearance of the player character (PC) in the game world (Figure 1), choices
that relate to game actions [69], commercial behaviour (e.g. buying digital goods
or aesthetic elements using real money or in-game digital currency) or interaction
with other players, usually using text chat, voice communication or even sign
language [10] capabilities.

An interesting trait of player-generated content is that, as research shows [8],
it is less controlled by social filters and inhibition; this effectively means that
players who participate and function within the safe sandbox of a digital game
world express themselves more vividly [15], using a wider range of spontaneous
emotions [25] and microexpressions [26] than usual affect- and emotion-related
interactions [23], thus offering richer input for AI/ML algorithms and cater-
Fig. 1. Example of User Generated Content, where players choose the appearance of their avatar.

Fig. 2. Example of User Generated Content, where players choose the appearance of their avatar.

Fig. 3. Example of User Generated Content, where players choose the appearance of their avatar.

An example of spontaneous user-generated content was presented in the Platformer Experience Dataset (or PED3) [24]. This is a multimodal dataset which contains videos of 58 participants playing IMB [66], an open-source clone of the popular “Super Mario Bros” platformer game (Figure 2), recordings of the game screen synchronised with the videos, logs of player actions with timestamps and a self-reported assessment of fun, interest and player experience in two forms, ratings and ranks (see [75] for an interesting discussion on ranking different choices or preferences, instead of rating each of them).

The approach of recording player expressivity along with player behaviour (actions in the game world) and player experience allows for a number of possible uses of AI/ML algorithms, either on recognition/classification or on generation of game content. For example, Asteriadis et al. combined head and body expressivity from players (Figure 2) with in-game actions to cluster them in different groups [3], taking also game performance and demographics into account [2]. An interesting observation of this work was that players often used microexpressions or microgestures in conjunction with their actions and the relevant movement of their character; for instance, they would nod in sync with jump actions or tilt their head to the direction of movement in response to avoiding an enemy. Clustering players with respect to expressivity and performance also identified

---

3 The dataset can be downloaded from https://ped.institutedigitalgames.com/
interesting patterns: for instance, expert players were either very expressive, in the sense that they were immersed in the game action and mimicked their character’s movement with body movements, or almost inanimate, indicating a high level of concentration. Overall, this work identified the need to combine player behaviour with expressive analysis so as to produce meaningful and dependable results regarding player engagement. In the same framework, Pedersen et al. produced levels for IMB which were predicted to be fun and engaging for each particular player, based on their affective and behavioural input while playing. This concept combines the sensing and player experience prediction work with modelling the aspects of the game level that make it hard, fun or irritating for each player: in the context of platform games, such as SMB or IMB, these factors include the number of gaps in a given level, the gap size, the number and placement of enemies and the positioning of rewards and power-ups. This work showed that by mapping player experience modelling with difficulty modelling, content generation algorithms can create individual game levels with a high degree of probability to be interesting and engaging.

Besides affective or audiovisual data of people playing games, the most relevant source of data comes from player behaviour (actions within the game world). The amount of data produced by players during gameplay differs with each genre, with turn-based or strategy games producing a few samples per minute and action games or Real-time Strategy (RTS) games providing hundreds of individual player actions per minute (APMs): in “Starcraft”, one of the most popular RTS games ever produced, top players typically record around 400
APMs in the preparation phase and close to 800 APMs during battle. As a result, accumulating large corpora of data and using them to train different AI/ML architectures has been a very popular use case for games and ML researchers. For example, Ravari et al. [44] utilise the datasets presented in [49] and [63] to predict the winner of each match, identifying relevant and important time-dependent (e.g. player actions, such as build or attack) and time-independent features, such as buildable areas in each game map or height of specific areas; to achieve this, they employ Gradient Boosting Regression Trees (GBRT) [16] and Random Forest (RF) [6] implementations in Scikit-learn, an open-source Python package. In the same context, Lin et al. produced a very large dataset of more than 65,000 games, which also includes visual information, besides player behaviour [30]; the sheer amount of data included here (1535 million frames, 496 million player actions) illustrates the relevance of player behaviour data to Big Data algorithms and processes (cf. [4] on churn prediction, i.e. when players quit playing a particular game, or [74] on how player behaviour data are processed in the game industry to promote player experience and spending behaviour)

A more contemporary source of data to be used with AI/ML algorithms comes from players interacting with other players during or before gameplay, in the form of text conversation (chat) or using voice. As mentioned earlier, gameplay eliminates most of the social inhibitions in players and allows for richer interaction and a wider variety of extreme emotions. Murnion et al. [35] utilise commercial sentiment analysis tools, such as Twinword Sentiment Analysis and Microsoft Azure Cognitive Services, to process player behaviour and game logs from an online multi-player game called World of Tanks (WoT); the authors are looking for positive vs. negative interactions and specific abusive behaviours, such as derogatory insults or racist attacks. An important aspect of this work is that it uses easily accessible services to retrieve, decrypt and process the data,
making the study easy to replicate and extend. The context of the study is also very interesting, since cyberbullying can result to extremely negative emotions and decisions, both with respect to players’ real lives, as well as their sense of attrition from the game: different studies have shown that more than 50% of players have either quit or considered quitting a game because of cyberbullying behaviours [17]. A similar approach regarding game data was used in [36], where authors used topic modelling and statistical analysis to analyse interactions between viewers (or spectators) of matches in Dota, a real-time multiplayer battle game. Their work identified patterns similar to those of football match spectators, especially in the case of intra-audience effects, despite the fact that audience commentary in eSports does not reach (and, hence, influence) the players directly.

3 Intelligent game content generation and selection

Game content generation has been a very active field in which AI/ML showcase their potential when it comes to generating data, mainly since the term content can refer to most audio, visual and narrative concepts in a game. Besides visual appearance, such as environment aesthetics or 2D/3D models of characters and environments, game content may refer to audio or aural media (e.g. the soundtrack of the game or specific audio effects used in response to game events, such as firing a weapon or player death), graphical user interfaces (GUI) [43], where interactive elements are used by the game to convey information (e.g. that another player or enemy is nearby) or by players to select game options and engage in game behaviour, or even the game narrative itself. The latter case ([21], [37], [50]) is extremely interesting, since it caters for the generation of different stories and games, based on an initial plan or narrative by the game designer. The success of narrative generation techniques in Role-Playing Games (RPGs), which are mainly popular in Japan, shows that this content generation option has the potential to create longer-lasting gameplay and keep players motivated, serving the needs of both researchers and the industry [60]. A special case of narrative generation includes NPC planning and behaviour [53], with content generation algorithms choosing and executing non-player character actions and dialogues based on virtual personalities (e.g. a sidekick or an enemy) or player behaviour (e.g. respond to the player ransacking a hut which belongs to a friendly villager in an RPG).

Intelligent content generation techniques can also be categorised with respect to the level of automation they require or provide. Some of those techniques enable designers to be involved in the process, either by initiating major changes in the way generated content is evolved [29] or by allowing players to adapt the content generated in the game [57]. Fully automated techniques [56], usually referred to as Procedural Content Generation (PCG), have been extremely popular with researchers, since they require little or no input, besides fine-tuning

---

4 A richer dataset that includes 50000 matches, game data, player skill ratings and chat can be found at https://www.kaggle.com/devianznelmo/dota-2-matches
the respective algorithm parameters, but they also enjoy success in commercial games: in the 1980’s, dungeon games such as *Akalabeth* and *Rogue* were among the first to use automatic (but sometimes random) content generation, while *Elite* (1985), a 3D space exploration game, used content generation to author 8 galaxies with 256 solar systems each and 1 to 12 planets in each solar system, all within 32Kb of code. Between *Diablo* (1995) and the recent years, PCG was mostly constrained to RPGs and dungeon layouts, with automatic content creation being revived by Minecraft (2011), developed by Mojang and now owned by Microsoft. More recent games include *Left for Dead* (2008) (instantiating game objects such as trees, monsters or treasures), *S.T.A.L.K.E.R.: The Shadow of Chernobyl* (2007) (dynamic systems create unscripted NPC behaviour), *Apophenia* (2008) (generation of puzzles and plots), and mainly *No Man’s Sky* (2016) with a procedurally generated deterministic open world universe and planets with unique flora and fauna (Figure 4), and various sentient alien species.

**Fig. 4.** Planet and environment generation in No Man’s Sky

Automatic PCG is usually matched with a respective generation algorithm and relevant constraints that match the game design or simply make sense. Vocabulary- or grammar-based generation algorithms are usually deployed to create game worlds, mazes or dungeons ([22]) and plants, whose recursive shape lends well to the way generation works in cellular automata ([33]) or L-systems ([67]). More recently, Müller et al. used L-systems to ([34]) to create 3D buildings with different sizes, number of rooms or floors. This is an interesting example, since the way the L-system is initially authored may reflect specific rules or constraints (e.g. to create a variety of structurally sound buildings in ([72])) or even be used to generate complete cities ([54]). Given the amount of polygonal geometry and texture images each building may require in a 3D environment, an automatic PCG algorithm that is able to create huge worlds with very little overhead in memory or CPU usage can replace the need to author the necessary
objects beforehand. This is also the case with algorithms based on Artificial Life approaches: BIOME is a programmable cellular automata simulator that allows users to develop simple “SimCity-like” grids, simulating phenomena such as forest fires, disease epidemics or animal migration patterns (cf. Figure 5).

When it comes to sequences of data to be generated, for instance in procedural music generation or when planning behaviours for NPCs, Hidden Markov Models (HMMs) are a usual choice. Snodgrass et al. [61] generated sequences of game levels for different platform games, comparing their performance in each one, while Plans et al. [42] combined generation with player experience to author the music score for a game. More recently, Long Short-Term Memory (LSTM) networks have been used to generate game levels, e.g. in a Super Mario Bros. clone [62]. LSTMs seem to have taken over the PCGML (Procedural Content Generation based on Machine Learning) experiments, thanks to the readily available implementations in Python and C#, as well as their recurrent nature that caters for generation of diverse and (theoretically) infinite content [48]. For instance, Savery and Weinberg [52] used LSTMs to synthesise musical scores based on image and video analysis, and Botoni et al. [5] to create NPCs with more depth in terms of dialogue and style.

---

5 Download BIOME from [http://www.spore.com/comm/prototypes](http://www.spore.com/comm/prototypes)
3.1 Generating content for a language education game

Generation of appropriate content for serious/educational games is an extremely important concept since it can make all the difference between adoption and retention of the game, thus increasing the possibility to achieve its learning objectives, and attrition [71]. In the iRead project\(^6\) we are creating a serious game and supporting applications for entry-level language learning of English, English as a Foreign Language (EFL), German, Spanish and Greek \(^5\). The core software applications developed in the project are a reader application\(^7\) which highlights parts of the words contained in the text, given specific criteria, and a serious game\(^8\) which consists of a series of gamified activities utilising words and sentences. The foundation of these applications and the software infrastructure that provides access to the content consists of language models for each language, including for children with dyslexia; following the definition of extensive phonological and syntactic models for these languages, the linguists in the project worked with teachers to define the learning objectives for each of the target age groups, as well as the sequence in which each language feature should be taught \(^{31}\). The sequencing of these features, including which prerequisites should be taught and mastered by the students before moving on to more advanced features, was encoded in a tree-like hierarchical graph; essentially, this graph encapsulates both the language model (i.e. the features that make up each word or sentence, at least at the given language level) and the teaching model, represented by the selection of necessary features for each school year and the succession in which they should be taught. When a new student registers with the iRead system, this graph is instantiated as a user profile, with different values of mastery for each feature, depending on the student’s age.

This is where the adaptive content generation component \(^6\) in iRead kicks in, first by utilising the mastery levels for each feature to select proper content from the project resource engine (dictionaries and texts) and then by updating the student’s model based on their performance in each language game they play; when the mastery level for a given feature surpasses a selected threshold (75%), subsequent features in the model hierarchy become available to play with, provided that all prerequisites for them have been met. In the context of iRead, the game content consists of selecting a particular game activity; a language feature to work with; and a set of words or a sentence that corresponds to that feature (e.g. a particular letter, phoneme or a sequence of phonemes).

The content selection process starts (cf. Figure 7 for an outline of the process) with the given student model, i.e. the mastery level for each open feature; then it selects the content for each session by filtering the available resources with a set of rules defined by project researchers after productive consultation sessions with the teachers collaborating with them. These rules were first defined in verbal form, in order to promote the teaching objectives of the games, with each of them corresponding to a particular pedagogical rationale. For instance, when

\(^6\) iRead project, https://iread-project.eu/
\(^7\) Amigo reader application, https://iread-project.eu/amigo-reader/
\(^8\) Navigo game, https://iread-project.eu/game/
multiple features are open (available to play with), the Adaptation component sorts them by taking into account how many times each of the features has been used in earlier games and how well the student has previously performed when presented with that feature. The reasoning here is that students should start from an easier feature and should not be playing a feature they have not done well with recently, thus fostering motivation and efficacy. Other rules attempt to reinforce learning by combining the feature mastery level achieved in previous games with the number of gameplay sessions since that feature was last used, and by reopening a fully mastered feature after ten games have been played since it was last used. The assumption is that the student has fully mastered that feature, but they must repeat it once in a while, to showcase their progress and long-term mastery. Finally, a number of feature selection rules deal with students not progressing as expected or not having truly mastered the language features which correspond to their age level: if a feature has been practised twice and the feature mastery is not improving, the mastery level for that feature and its prerequisites is reduced, so that both can be revisited in future sessions. This content selection strategy treats the assumption that students in a given age group have already mastered certain language features, by allowing them to go back to required knowledge, if there is no system evidence that it has been acquired. In addition to selecting proper word content, the iRead adaptivity system utilises a rule-based strategy to select specific game activities to utilise those words: if a feature has not been previously used in a game for the particular
student, then the selected game should promote accuracy in using that language characteristic, before moving on to games which stimulate automaticity.

The second part of the adaptation component in iRead has to do with re-evaluating the value of mastery for the language feature used in a game. During the consultation sessions, teachers mentioned a number of requirements for this process: changes in mastery values should not be abrupt, especially when students make an occasional error in one of the activities; besides this, they should help students demonstrate complete mastery of a feature within a handful of gaming sessions, allowing them to move on to more advanced and interesting features. A mathematical definition that accommodates these requirements, while leaving room for experimentation and adjustments of the process, is that of Exponential Moving Average (EMA) [40]: essentially, this takes into account previous attempts at a particular feature (previous game sessions) but gives more weight to recent attempts. The number of previous attempts to consider may be defined by each implementation; in iRead, we implemented the complete definition, but chose to consider only the previous value of mastery, when calculating the next one. This averaging process allows students to show complete mastery in just three games, since each newly opened feature is initialised with a value of 5 and after three perfect games reaches the maximum value of 10. In addition, in case the student makes one or more errors during game play, the respective
mastery value may be reduced by 1 at maximum. This mechanic, along with the rules which prioritise features given the recent gameplay attempts, allows students to practise different language content, without being stuck with difficult features.

On-going evaluation ([7], [47]) has shown that the automated content selection and the profile re-evaluation processes are quite close to what teachers expect and provide suitable and interesting content for the students. Even though the re-evaluation mechanic allows unlocking subsequent features quite easily, there have been reports that students are being given the same features to play with during numerous successive game sessions. However, after going through the system logs of gameplay results and mastery evaluations, we reached the conclusion that this reflects the design of the respective language model, which imposed a large number of prerequisites to be unlocked before moving on to more complex features. This effectively illustrates the interplay between the different iRead components: the features which describe each language model, the graph of prerequisites which describes the sequencing embedded in the learning process, the mastery levels for each feature which reflect student performance, and the adaptation and re-evaluation rules described above, which prioritise content to implement teaching objectives.

The large-scale evaluation phase in schools across Europe is already underway, with more than 2000 students taking part. Even though it has been disrupted by the pandemic and schools closing down, we expect gameplay logs to keep coming in from students playing the games at home. Processing these logs will allow us to revisit specific parts of the adaptation component, primarily the content selection rules and the mastery re-evaluation implementation.

4 Conclusions

The interplay between AI/ML algorithms and digital games has been in the forefront of scientific news and research outlets for the past few years. The main reason for this is that it fosters adaptive player experiences [76], which promote and even maximise fun and engagement. Besides this, AI/ML can be used to select and generate diverse and related game content, even from sources of Open and Big Data (cf. [70] for a Monopoly clone populated with Open Data [65] to teach Big Data rankings and associations in the context of a primary school geography course or [13] for an approach that uses Open Data in a card game for environmental education), making games more relevant to everyday life. In this chapter, we outlined some of the more prominent approaches which combine AI/ML with game design concepts and player behaviour to provide information about player experience and generate content that’s predicted to maximise engagement. We also described an approach to estimate player experience and engagement based on behaviour and affective expressivity during gameplay and an intelligent algorithm that generates language content for a serious game, based on player performance and learning/teaching objectives. As users provide more and richer input to AI/ML algorithms through explicit choices and gameplay,
it is expected that this interplay will become even more meaningful and will be integrated in more applications, expanding into education, inclusion [54] and gamification ([27], [28]).

Acknowledgements This work has been partly funded by the iRead project which has received funding from the European Union’s Horizon 2020 Research and Innovation programme under Grant Agreement No. 731724.

References

1. Alba Amato. Procedural content generation in the game industry. In Game Dynamics, pages 15–25. Springer, 2017.
2. Stylianos Asteriadis, Kostas Karpouzis, Noor Shaker, and Georgios N Yannakakis. Does your profile say it all? using demographics to predict expressive head movement during gameplay. 2012.
3. Stylianos Asteriadis, Kostas Karpouzis, Noor Shaker, and Georgios N Yannakakis. Towards detecting clusters of players using visual and gameplay behavioral cues. Procedia Computer Science, 15:140–147, 2012.
4. Paul Bertens, Anna Guigart, and África Periáñez. Games and big data: A scalable multi-dimensional churn prediction model. In 2017 IEEE conference on computational intelligence and games (CIG), pages 33–36. IEEE, 2017.
5. Brooke Bottini, Yasmine Moolenaar, Anthony Hevia, Thomas Anchor, Kyle A Benko, Rainer Knauf, Klaus P Jantke, Avelino J Gonzalez, and Annie S Wu. Character depth and sentence diversification in automated narrative generation. In FLAIRS Conference, pages 21–26, 2020.
6. Leo Breiman. Random forests. Machine learning, 45(1):5–32, 2001.
7. Leona Bunting, Ylva Hård af Segerstad, and Wolmet Barendregt. Swedish teachers’ views on the use of personalised learning technologies for teaching children reading in the english classroom. International Journal of Child-Computer Interaction, 27:100236, 2021.
8. Paul Cairns, Anna L Cox, Matthew Day, Hayley Martin, and Thomas Perryman. Who but not where: The effect of social play on immersion in digital games. International Journal of Human-Computer Studies, 71(11):1069–1077, 2013.
9. Murray Campbell, A Joseph Hoane Jr, and Feng-hsiung Hsu. Deep blue. Artificial intelligence, 134(1-2):57–83, 2002.
10. George Caridakis, Stylianos Asteriadis, and Kostas Karpouzis. Non-manual cues in automatic sign language recognition. Personal and ubiquitous computing, 18(1):37–46, 2014.
11. Elin Carstensdottir, Erica Kleinman, and Magy Seif El-Nasr. Player interaction in narrative games: structure and narrative progression mechanics. In Proceedings of the 14th International Conference on the Foundations of Digital Games, pages 1–9, 2019.
12. Darryl Charles and Benjamin Ualtan Cowley. Behavlet analytics for player profiling and churn prediction. In International Conference on Human-Computer Interaction, pages 631–643. Springer, 2020.
13. Domna Chiotaki and Kostas Karpouzis. Open and cultural data games for learning. arXiv preprint arXiv:2004.07521, 2020.
14. Roddy Cowie, Cate Cox, Jean-Claude Martin, Anton Batliner, Dirk Heylen, and Kostas Karpouzis. Issues in data labelling. In Emotion-oriented systems, pages 213–241. Springer, 2011.

15. K. Durning, Jackson College of Graduate Studies, and Jackson College of Graduate Studies. Department of Psychology. Gaming Relationship to Social Psychology and Micro-expressions. University of Central Oklahoma, 2016.

16. Jerome H Friedman. Stochastic gradient boosting. Computational statistics & data analysis, 38(4):367–378, 2002.

17. Meg Fryling, Jami Lynn Cotler, Jack Rivituso, Lauren Mathews, and Shauna Pratico. Cyberbullying or normal game play? impact of age, gender, and experience on cyberbullying in multi-player online gaming environments: Perceptions from one gaming forum. Journal of Information Systems Applied Research, 8(1):4, 2015.

18. Sofia Gourgari, Georgios Goudelis, Konstantinos Karpouzis, and Stefanos Kollias. Thetis: Three dimensional tennis shots a human action dataset. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pages 676–681, 2013.

19. Christian Guckelsberger, Christoph Salge, Jeremy Gow, and Paul Cairns. Predicting player experience without the player. an exploratory study. In Proceedings of the Annual Symposium on Computer-Human Interaction in Play, pages 305–315, 2017.

20. Scott H Hemenover and Nicholas D Bowman. Video games, emotion, and emotion regulation: Expanding the scope. Annals of the International Communication Association, 42(2):125–143, 2018.

21. Shohei Imabuchi and Takashi Ogata. A story generation system based on propp theory: As a mechanism in an integrated narrative generation system. In International Conference on NLP, pages 312–321. Springer, 2012.

22. Lawrence Johnson, Georgios N Yannakakis, and Julian Togelius. Cellular automata for real-time generation of infinite cave levels. In Proceedings of the 2010 Workshop on Procedural Content Generation in Games, pages 1–4, 2010.

23. Kostas Karpouzis and Georgios N Yannakakis. Emotion in Games. Springer, 2016.

24. Kostas Karpouzis, Georgios N Yannakakis, Noor Shaker, and Stylianos Asteriadis. The platformer experience dataset. In 2015 International Conference on Affective Computing and Intelligent Interaction (ACII), pages 712–718. IEEE, 2015.

25. Irene Kotsia, Stefanos Zafeiriou, George Goudelis, Ioannis Patras, and Kostas Karpouzis. Multimodal sensing in affective gaming. In Emotion in Games, pages 59–84. Springer, 2016.

26. Greg Lastowka. User-generated content and virtual worlds. Vand. J. Ent. & Tech. L., 10:893, 2007.

27. Nikoletta Zampeta Legaki, Kostas Karpouzis, and Vassilios Assimakopoulos. Using gamification to teach forecasting in a business school setting. In GamiFIN, pages 13–24, 2019.

28. Nikoletta-Zampeta Legaki, Nannan Xi, Juho Hamari, Kostas Karpouzis, and Vassilios Assimakopoulos. The effect of challenge-based gamification on learning: An experiment in the context of statistics education. International journal of human-computer studies, page 102496, 2020.

29. Antonios Liapis, Gillian Smith, and Noor Shaker. Mixed-initiative content creation. In Procedural content generation in games, pages 195–214. Springer, 2016.

30. Zeming Lin, Jonas Gehring, Vasil Khalidov, and Gabriel Synnaeve. Stardata: A starcraft ai research dataset. arXiv preprint arXiv:1708.02139, 2017.
31. Manolis Mavrikis, Asimina Vassalou, Laura Benton, Chrysanthi Raftopoulou, Antonios Symvonis, Kostas Karpouzis, and Drew Wilkins. Towards evidence-informed design principles for adaptive reading games. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, pages 1–4, 2019.

32. Tian Min and Wei Cai. A security case study for blockchain games. In *2019 IEEE Games, Entertainment, Media Conference (GEM)*, pages 1–8. IEEE, 2019.

33. Sajed Miremadi, Bengt Lennartson, and Knut Akesson. A bdd-based approach for modeling plant and supervisor by extended finite automata. *IEEE Transactions on Control Systems Technology*, 20(6):1421–1435, 2011.

34. Pascal Müller, Peter Wonka, Simon Haegler, Andreas Ulmer, and Luc Van Gool. Procedural modeling of buildings. In *ACM SIGGRAPH 2006 Papers*, pages 614–623, 2006.

35. Shane Murnion, William J Buchanan, Adrian Smales, and Gordon Russell. Machine learning and semantic analysis of in-game chat for cyberbullying. *Computers & Security*, 76:197–213, 2018.

36. Ilya Musabirov, Denis Bulygin, Paul Okopny, and Ksenia Konstantinova. Between an arena and a sports bar: Online chats of esports spectators. *arXiv preprint arXiv:1801.02862*, 2018.

37. Takashi Ogata. Building conceptual dictionaries for an integrated narrative generation system. *Journal of Robotics, Networking and Artificial Life*, 1(4):270–284, 2015.

38. Dionysis Panagiotopoulos and Antonios Symvonis. iread: Infrastructure and integrated tools for personalized learning of reading skill. *Information, Intelligence, Systems and Applications*, 1(1):44–46, 2020.

39. Christopher Pedersen, Julian Togelius, and Georgios N Yannakakis. Modeling player experience for content creation. *IEEE Transactions on Computational Intelligence and AI in Games*, 2(1):54–67, 2010.

40. Radek Pelánek and Jiří Řihák. Experimental analysis of mastery learning criteria. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization*, pages 156–163, 2017.

41. Bernard Perron. A cognitive psychological approach to gameplay emotions. 2005.

42. David Plans and Davide Morelli. Experience-driven procedural music generation for games. *IEEE Transactions on Computational Intelligence and AI in Games*, 4(3):192–198, 2012.

43. Roman Popp, David Raneburger, and Hermann Kaindl. Tool support for automated multi-device gui generation from discourse-based communication models. In *Proceedings of the 5th ACM SIGCHI symposium on Engineering interactive computing systems*, pages 145–150, 2013.

44. Yaser Norouzzadeh Ravari, Snader Bakkes, and Pieter Spronck. Starcraft winner prediction. In *Twelfth artificial intelligence and interactive digital entertainment conference*, 2016.

45. Jon Peddie Research. *eSports is a Driving Force Behind PC Gaming Hardware Sales Growth*, 2017 (accessed September 3, 2020). [https://www.globenewswire.com/news-release/2017/07/11/1042645/0/en/JPR-eSports-is-a-Driving-Force-Behind-PC-Gaming-Hardware-Sales-Growth.html](https://www.globenewswire.com/news-release/2017/07/11/1042645/0/en/JPR-eSports-is-a-Driving-Force-Behind-PC-Gaming-Hardware-Sales-Growth.html).

46. Pew Research. *5 facts about Americans and video games*, 2018 (accessed September 3, 2020). [https://www.pewresearch.org/fact-tank/2018/09/17/5-facts-about-americans-and-video-games/](https://www.pewresearch.org/fact-tank/2018/09/17/5-facts-about-americans-and-video-games/).
47. A. Révézsi, M. Vasalou, A. Florea, R. Gilabert, Leona Bunting, Ylva Hrd af Segerstad, Ioan Mihu, C. Parry, and L. Benton. The effects of textual enhancement on development in L2 derivational morphology: A multi-site longitudinal study. 2020.

48. Sebastian Risi and Julian Togelius. Procedural content generation: from automatically generating game levels to increasing generality in machine learning. arXiv preprint arXiv:1911.13071, 2019.

49. Glen Robertson and Ian Watson. An improved dataset and extraction process for starcraft ai. In The Twenty-Seventh International Flairs Conference. Citeseer, 2014.

50. Justus Robertson and Robert Michael Young. Automated gameplay generation from declarative world representations. In AIIDE, pages 72–78, 2015.

51. Saeed Shafiee Sabet, Steven Schmidt, Saman Zadtootaghaj, Carsten Griwodz, and Sebastian Moller. Towards the impact of gamers strategy and user inputs on the delay sensitivity of cloud games. In 2020 Twelfth International Conference on Quality of Multimedia Experience (QoMEX), pages 1–3. IEEE, 2020.

52. Richard Savery and Gil Weinberg. Shimon the robot film composer and deepscore: An lstm for generation of film scores based on visual analysis. arXiv preprint arXiv:2011.07953, 2020.

53. Anthony Savidis. There is more to pcg than meets the eye: Npc ai, dynamic camera, pvs and lightmaps. arXiv preprint arXiv:1808.00328, 2018.

54. Alexander Schmölz, Kostas Karpouzis, Daniel Pfeiffer, and Pavlos Koulouris. Doing social inclusion: Aiming to conquer crisis through game-based dialogues and games.

55. Noor Shaker, Stylianos Asteriadis, Georgios N Yannakakis, and Kostas Karpouzis. A game-based corpus for analysing the interplay between game context and player experience. In International Conference on Affective Computing and Intelligent Interaction, pages 547–556. Springer, 2011.

56. Noor Shaker, Julian Togelius, and Mark J. Nelson. Procedural Content Generation in Games: A Textbook and an Overview of Current Research. Springer, 2016.

57. Noor Shaker, Georgios N. Yannakakis, and Julian Togelius. Towards player-driven procedural content generation. In Proceedings of the 9th Conference on Computing Frontiers, CF ’12, page 237–240, New York, NY, USA, 2012. Association for Computing Machinery.

58. David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. nature, 529(7587):484–489, 2016.

59. David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, et al. A general reinforcement learning algorithm that masters chess, shogi, and go through self-play. Science, 362(6419):1140–1144, 2018.

60. Gillian Smith, Elaine Gan, Alexei Othenin-Girard, and Jim Whitehead. Pcg-based game design: enabling new play experiences through procedural content generation. In Proceedings of the 2nd International Workshop on Procedural Content Generation in Games, pages 1–4, 2011.

61. Sam Snodgrass and Santiago Ontanón. Learning to generate video game maps using markov models. IEEE transactions on computational intelligence and AI in games, 9(4):410–422, 2016.
62. Adam Summerville, Sam Snodgrass, Matthew Guzdial, Christoffer Holmgård, Amy K Hoover, Aaron Isaksen, Andy Nealen, and Julian Togelius. Procedural content generation via machine learning (pcgml). *IEEE Transactions on Games*, 10(3):257–270, 2018.

63. Gabriel Synnaeve and Pierre Bessiere. A dataset for starcraft ai & an example of armies clustering. 2012.

64. Jerry O Talton, Yu Lou, Steve Lesser, Jared Duke, Radomír Mích, and Vladlen Koltn. Metropolis procedural modeling. *ACM Transactions on Graphics (TOG)*, 30(2):1–14, 2011.

65. Stamatios Theocharis and George A Tsihrintzis. Ontology development to support the open public data-the greek case. In *IISA 2014, The 5th International Conference on Information, Intelligence, Systems and Applications*, pages 385–390. IEEE, 2014.

66. Julian Togelius, Sergey Karakovskiy, and Robin Baumgarten. The 2009 mario ai competition. In *IEEE Congress on Evolutionary Computation*, pages 1–8. IEEE, 2010.

67. Julian Togelius, Noor Shaker, and Joris Dormans. Grammars and l-systems with applications to vegetation and levels. In *Procedural Content Generation in Games*, pages 73–98. Springer, 2016.

68. G. Tsatiris and K. Karpouzis. Developing for personalised learning: the long road from educational objectives to development and feedback. ACM Interaction Design and Children (IDC) conference 2020, workshop on Technology-mediated personalized learning for younger learners: concepts, methods and practice, 2020.

69. George A Tsihrintzis, Dionisios N Sotiropoulos, and Lakhmi C Jain. Machine learning paradigms: Advances in data analytics. In *Machine Learning Paradigms*, pages 1–4. Springer, 2019.

70. Irene Vargianniti and Kostas Karpouzis. Using big and open data to generate content for an educational game to increase student performance and interest. *Big Data and Cognitive Computing*, 4(4):30, 2020.

71. Maria Virvou, George Katsionis, and Konstantinos Manos. Combining software games with education: Evaluation of its educational effectiveness. *Journal of Educational Technology & Society*, 8(2):54–65, 2005.

72. Emily Whiting, John Ochsendorf, and Frédéric Durand. Procedural modeling of structurally-sound masonry buildings. In *ACM SIGGRAPH Asia 2009 papers*, pages 1–9. 2009.

73. Josef Wiemeyer, Lennart Nacke, Christiane Moser, et al. Player experience. In *Serious Games*, pages 243–271. Springer, 2016.

74. Michele Willson and Tana Leaver. Zynga’s farmville, social games, and the ethics of big data mining. *Communication Research and Practice*, 1(2):147–158, 2015.

75. Georgios N Yannakakis, Roddy Cowie, and Carlos Busso. The ordinal nature of emotions. In *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*, pages 248–255. IEEE, 2017.

76. Georgios N Yannakakis, Katherine Isbister, Ana Paiva, and Kostas Karpouzis. Guest editorial: Emotion in games. *IEEE Trans. Affective Computing*, 5(1):1–2, 2014.