

# The Case for Usable AI: What Industry Professionals Make of Academic AI in Video Games

Johannes Pfau  
University of Bremen  
Germany  
jpfau@tzi.de

Jan David Smeddinck  
Newcastle University  
Newcastle upon Tyne, UK  
jan.smeddinck@newcastle.ac.uk

Rainer Malaka  
University of Bremen  
Germany  
malaka@tzi.de

## ABSTRACT

Artificial intelligence (AI) is a frequently used term – and has seen decades of use – in the video games industry. Yet, while academic AI research recently produced notable advances both in different methods and in real-world applications, the use of modern AI techniques, such as deep learning remains curiously sparse in commercial video games. Related work has shown that there is a notable separation between AI in games and academic AI, down to the level of the definitions of what AI is and means. To address the practical barriers that sustain this gap, we conducted a series of interviews with industry professionals. The outcomes underline requirements that are often overlooked: While academic (games) AI research tends to focus on problem-solving capacity, industry professionals highlight the importance of “usability aspects of AI”: the ability to produce plausible outputs (effectiveness), computational performance (efficiency) and ease of implementation (ease of use).

## CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence.**

## KEYWORDS

Video games; industry; survey

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## 1 INTRODUCTION

Due to its steady growth in popularity and accessibility, the video game industry has evolved into a multi-billion dollar sector that surpassed all other entertainment industry areas, including TV, cinema and music<sup>1</sup>. Along with this development, the industry is constantly advancing, harnessing progress – or even trying to build

<sup>1</sup><https://newzoo.com/insights/trend-reports/newzoo-global-games-market-report-2019-light-version/>. Accessed 3.7.2020

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a competitive edge based on innovations – in various fields, e.g. visual rendering, player experience, network stability or hardware progression. However, when it comes to *artificial intelligence* (AI) methods, only a small minority of shipped games harnesses recent scientific advancements [31, 37]. Large proportions of video games involve strategic decision making, optimization processes or competition, which make up fertile exploration grounds for AI, while many games even accumulate the vast amounts of data required for e.g. deep learning techniques. This is constantly demonstrated by successful integration examples, where – in the reverse direction – scientific research on AI for games frequently builds on industrial games, as in game playing [1, 17, 35], automated testing [22, 26, 34] or balancing [9, 20], world-building [27, 36], dynamic difficulty adjustment (DDA) [8, 24, 25] or player modeling [7, 19, 21, 23]. Yet, few cases of scientific AI have been applied in commercially successful video games, most of the time only when the AI itself constitutes part of the game’s core mechanics [37], such as in the reinforcement learning of the companion animal in *Black and White* [12], the DDA features in *Halo*<sup>2</sup> [2] or *Left 4 Dead* [33] or the imitation learning (*Drivatar*) of *Forza Motorsport* [32]. This notable disparity can be related to the significantly differing definitions between scientific and industrial game AI. While a definition for scientific AI may be expressed as “*the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages*”<sup>3</sup>, in the context of video games AI is more frequently seen along the lines of: “*artificial intelligence consists of emulating the behavior of other players or the entities [...] they represent. The key concept is that the behavior is simulated. In other words, AI for games is more artificial and less intelligence. The system can be as simple as a rules-based system or as complex as a system designed to challenge a player as the commander of an opposing army*” [10]. While this may partially be the result of different evolutions of understandings and the applied development of AI, it can arguably also contribute as a potential cause to forming and maintaining considerably isolated spheres of different understandings and schools of AI.

Additionally, due to market-forces in industry, information about utilized algorithms and techniques is not explicitly detectable and often not published for reasons of intellectual property and exploitation avoidance. To investigate the stance of AAA-developers on integrating promising AI techniques into video games, we contacted 105 of the currently most successful game companies, asking to conduct a semi-structured interview concerning their current use

<sup>2</sup>[http://www.gamasutra.com/gdc2005/features/20050311/isla\\_01.shtml](http://www.gamasutra.com/gdc2005/features/20050311/isla_01.shtml). Accessed 3.7.2020.

<sup>3</sup>[https://en.oxforddictionaries.com/definition/artificial\\_intelligence](https://en.oxforddictionaries.com/definition/artificial_intelligence). Accessed 3.7.2020

and requirements for applicable AI. This paper contributes to game research and development in academia and industry by providing a qualitative analysis of ( $n = 9$ ) industrial developers as well as derived guidelines that AI techniques can build on in order to be considered applicable.

## 2 RELATED WORK

Makridakis [13], as well as Skilton [28], predict that video games businesses will be highly impacted by the rise of deep learning and the embedding of AI in more and more facets of daily routine. Frutos et al. review the implementation of AI techniques within the scope of the serious game genre and point out a lack of applied AI methods, even if most of the applications originated in academia [4]. Togelius highlights the value of video games as ideal testbeds for academic AI, while on the other hand, this AI could significantly improve game mechanics and player experience [31]. According to Yannakakis, the sparse deployment within industrial productions is mainly caused by *“the lack of constructive communication between academia and industry in the early days of academic game AI, and the inability of academic game AI to propose methods that would significantly advance existing development processes or provide scalable solutions to real world problems”* [37]. Lara-Cabrera et al. note that the industry is beginning to *“adopt the techniques and recommendations academia offers”*, based on public reports from the respective companies [11].

All of these accounts reflect missed opportunities of the industry and incorporate or introduce methods that could fit into industrial implementation, yet no official statements from the actual target group (i.e. industry representatives) have been included so far. We argue that including explicit industry voice can contribute to achieving less one-sided discussions. Therefore this work aims to start contributing to closing this unresolved gap by providing qualitative insights from video game industry professionals based on a semi-structured interview concerning academic game AI.

## 3 STUDY

In order to obtain a broad impression of the industry’s stance on scientific AI, 105 of the currently most successful game companies were contacted for a digital, semi-structured interview. After a period of six weeks and two additional reminders, ( $n = 9$ ) responses could be collected that served for an outcome-oriented structuring content analysis [15].

### 3.1 Measures

Initially, participants stated their affiliated game project(s) and company. Subsequently, they were asked about the AI methods that are frequently utilized for development or game mechanics within their projects, followed by details about the type of algorithm or implementation. Beyond this, they stated their personal opinion with respect to the use of further AI techniques and outlined reasons why these are not (yet) incorporated.

### 3.2 Procedure

Companies were approached through publicly available contact points such as general inquiry mail addresses or instant messengers of community contacts. To avoid demanding personal information or addresses of the developers in order to allow less constrained

reflection, the participation requests contained a request to be forwarded internally to representatives for game AI, machine learning, data analysis or development in general. Following informed consent, participants were able to express themselves freely within an online survey. Eventually, they were free to submit name and affiliation or to anonymize their participation.

### 3.3 Participants

In total, ( $n = 9$ ) participants of at least seven different companies (including *Croteam*, *Crytek*, *Obsidian Entertainment*, *Paradox Development Studio*, *Harebrained Schemes*) completed the digital survey. Three of these decided to submit their data anonymously.

## 4 OUTCOMES

All of the surveyed participants agreed that the successful integration of pathfinding in more or less every modern video game since algorithms like A\* [5] are cheap in computation, reliable and compelling, conditions which were relayed as clear requirements for consumer environments. Furthermore, unlike many of the other fields of AI, pathfinding is essential for video games to prevent totally idiosyncratic behavior, which led to a very early establishment in the industry. Another frequently mentioned technique are *Finite State Automata* (FSA) [16], for their robustness and observability, despite lacking any higher level capability of reasoning. Developers state that they use them for *“Movement state machines, etc.”* (P6), *“Character action sequences and combat”* (P4) or *“a lot of tasks not considered AI, like managing states of User Interface widgets”* (P3), fulfilling predictable tasks far removed from the potential of more elaborate AI approaches. *Dynamic difficulty adjustment* [8, 30] is reportedly roughly applied with heuristics like *“[opponents] will start to miss more after managing to hit the player too rapidly”* (P6), while the same holds also for reasoning systems, which are mostly reduced to frugal decision making about movement (*“e.g. to find out what a good position to shoot from will be, considering things like line-of-fire, distance to target, minimal distance from current position, closeness to allies, etc.”*) (P7), *“Most of our AI is still reactive, but we have systems that ‘sample’ positions in the world for things like: get good attack position, cover spot, etc”* (P6). Knowledge bases for NPC are elementary but common, incorporating known versus unknown facts, e.g. in *“computer player’s knowledge of the game state (where other units are on the map)”* (P3). *Procedural Content Generation* (PCG) has found its place in the game industry, not least because of games that are completely centered around it (e.g. *Minecraft* [18], *Spore* [14] or *No Man’s Sky* [6]), but also in regular games that are not completely focused on PCG, mostly for *“Worldbuilding”* (P2) or *“[generating] in-game content, like making trees at design time”* (P3). Multi-agent interaction is stated to be a discipline that can improve game quality in a thorough manner, which is why many companies try to come up with good solutions, e.g. *“NPCs can decide to perform a complex attack together”* (P4), *“One AI charges a player, while the team members give covering fire”* (P6), albeit drawing on FSA for these decisions. The reasons for the sparse and conservative use of academic AI are shared among the industry:

*“So far, our AI systems are mostly reactive and driven by behavior trees [3] that receive signals from events that happen in the world. The reason for this is that we*

*need to model explicit rules in their behaviors to make the AI readable and “fun” for the player. Also, we need to do this using **limited CPU bandwidth** and in a way that these systems are **debuggable**” (P6).*

When asked about their personal position with respect to academic AI, they agreed that it bears a considerable potential and is of interest (for both developers and players). They also attribute capabilities for making the environment more believable, yet the surveyed experts are weary that academic AI comes with a notable implementation and configuration effort that typically result in the industry focusing on heuristic workarounds. According to our sample, the underlying mindset is best summarised in the terms of the surveyed professionals, implicitly reflecting requirements of the industry:

*“What we call “AI” in games is vastly different than what’s used in academia, or in business/ engineering/ apps/ ... Due to specific requirements like suspension of disbelief, games need a tighter control of possible outcomes and cannot afford the situation to be wildly misinterpreted. [...] Using decision trees, goal oriented action planning<sup>4</sup>, and similar is found in some games, but we still largely rely on hand-tuned conditions controlled by hard-coded ifs, state machines etc. If you care more about “**plausibility**” than “intelligence”, experience shows that hand-tuned solutions go a long way further than emergent ones. Also, consider the fact that **performance** budget is severely limited especially if there’s a large number of actors. E.g we once experimented with a very elaborate goal-oriented action planning algorithm heuristic for gunfight tactics (choosing cover, targets, ....) where things like e.g. flanking were emergent results of the simple base logic resting on data like cover positions, precision estimation, etc... The results were impressive, but way too expensive. [They] could still produce unexpected results in some cases. When you consider that most games in that genre do away with prescribed actions for each possible scene, saving an order of magnitude on performance - and guaranteeing no unexpected behavior, you realize that there’s still a long way to go for “real AI” in games.” (P1)*

Apart from that, several participants highlighted the considerable labor effort that comes with implementation, adjustment and quality assurance:

*“In order to make AI a noticeable feature where towns are full of interacting NPCs or where enemies are executing complex strategy, a company has to dedicate probably a dozen or more programmers/designers for over a year to set it all up, which is **very expensive**. Also, the more complex the AI, the more bugs that are created which reduces the polish of the game. We would love to have awesome villager AI with life like daily routines, but it’s just too cost prohibitive.” (P4)*

P5 brings up that industry and academic AI pursue different goals and that scientific advances do not necessarily lead to improved player experiences:

*“As game AI is focused on creating entertainment rather than primarily solve problems (which academic AI typically does), and usually has much stricter constraints on **performance** than academic AI, it is often faster to custom-build solutions rather than use academic approaches. It also appears to be largely cheaper to produce a solution that fits the game and is “correct enough” than actually implement a method that produces a correct result. I think for most game AI developers, the interest in using academically developed AI goes as far as it can improve specifics in AI behaviour **reliably** and within budget (both development resources as well as CPU and memory).” (P5)*

Eventually, in order to actually ensure an improved player experience, developers conclude that this works best when AI techniques constitute central game mechanics, so that players actually perceive the added value:

*“I think there are some opportunities to do more “advanced” AI in video games, but, it probably means that these games needs to be build and designed “around” these systems to make them really shine.” (P6)*

## 5 DISCUSSION

Overall, the responses to the survey gave uniform insights on which AI techniques are popular, suitable or even necessary for modern games (e.g. pathfinding, FSA, PCG) and why other academic advancements are not trivial to adapt for the industry yet (e.g. machine learning, multi-agent reasoning systems, natural language processing). Summarized, the recorded statements can inform the development of more applicable academic AI techniques, e.g. through adding purpose-build middle-ware / services, by providing design guidelines that expect **plausibility/believability**, **computational performance** and **ease of implementation** in order to be applicable and recognized by the industry. These factors notably relate to the foundations of usability in efficiency, effectiveness and ease of use [29]. Ideally, these approaches should also be evaluated for **player experience** to justify the considerable effort and estimate the impact and implications on the game and its players. In effect, scientific submissions that contribute or benchmark novel AI techniques and aim to provide solutions that are applicable in industry, or translational research that aims to investigate the applicability of existing AI techniques in real-world contexts should evaluate and report their applicability with reference to these design requirements beyond the more common focus on successful problem-solving.

## 6 LIMITATIONS AND FUTURE WORK

The most notable limitation of this work remains the small number of interviewed experts, due to a considerably sparse response rate. Following from this, the interviewed companies will likely not cover all video game genres, and based on the publicly visible profiles are constrained to represent (offline) first-person shooters

<sup>4</sup><http://alumni.media.mit.edu/~jorkin/goap.html> . Accessed 3.7.2020

(FPS), role playing games (RPGs) and real-time as well as turn-based strategy games. While it can be argued that most of the mentioned issues and requirements can also be found in e.g. online FPS, massively multiplayer online RPGs or multiplayer online battle arenas (MOBAs), we aim to extend this study to a larger group. An additional bias might have been the recruitment method of the participants, as developers only answered if they had the temporal capacity, the company policy allowed the publication of inside knowledge and they were able to follow and answer the English language of the study. In the follow-up evaluation, we are looking forward to working with a group of experts that is large enough to amount to a meaningful sample that is more representative for the industry and the diverse requirements of different genres, as well as to include quantitative measures and supplementary sources of information, such as public industry reports (e.g. *Gamasutra*<sup>5</sup>, blog entries, or the Game AI Summit from the *Game Developers Conference*<sup>6</sup>).

## 7 CONCLUSION

Academic (game) AI researchers agree that video games provide expedient testbeds for algorithms, benchmarks and data aggregation, while video games could simultaneously benefit from the considerable advancements academic (game) AI continues to establish. Nevertheless, the use of modern and advanced AI techniques by video game companies remains limited, if the resulting games are not explicitly centered around these techniques. Using qualitative semi-structured interviews, this paper reveals the most crucial reasons cited by industry professionals and subsequently extracts requirements that novel AI approaches should meet in order to be applicable for industrial use. Developers expect that AI does not harm the **plausibility/believability** of NPCs (but ideally elevates it), the techniques have to be **easy to implement**, debug and adjust, they should not increase the game's **computational performance** requirements significantly and the added value of **player experience** should be proven. This work contributes to game AI research and development in academia and industry in pursuit of a closer integration of both areas.

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