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Review and analysis of research on Video Games and Artificial Intelligence: a look back and a step forward

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Abstract

This article shows the intimate relationship between Artificial Intelligence (AI) and video games research in 13 categories of analysis based on a bibliometric survey carried out in the Scopus database. We first briefly reviewed the relation between video games and AI. Then, we introduced the methodology of literature collection, presented and discussed the query, as well the flow of data treatment in the applications and plugins used. Since the article is concerned with a historical point of view of the relationship between digital games and AI the results were many and, therefore, we focused on the top 10 of each ranking, and discussed these results separately. Finally, we discuss the limitations of our review, proposing future research directions for scholars.

Keywords: *Computer games; AI; Games, Bibliometric analysis, Virtual Reality.*

1. Introduction

Since the beginning of AI, it has been related to games [1]. These games were fundamentally used to measure the ability and performance of the AI. In 1950 Shannon shared the main aspects of computational routine in the article

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"Programming a computer for playing chess" [1]. The paper introduces a process for the computer to be able to decide which move to perform next. For this, the minimax procedure was used, based on an evaluation function of a certain chess position.

In 1952 a British professor of computer science, Alexander Douglass, created the OXO game also known as tic-tac-toe, as part of his Ph.D. research on human-computer interaction for the University of Cambridge. OXO was a single-player game in which one player plays against the computer. The first computer game is generally assumed to be "Spacewar!", developed in 1962 at MIT. Pac-Man, a simple arcade game from 1981 introduced different AI heuristics to each one of the four ghosts of the game, creating personalities for these enemies. The first sequel of Pac-Man, Ms. Pac-Man, released in 1982, is more challenging and according to [2] the version Ms. Pac-Man vs. Ghosts is a preference for the current AI's competitions since it supports the two main approaches to train videogame bots: Genetic Algorithms and Reinforcement Learning. There is a common criticism about game AI, based on its objective, that this kind of AI needs only to look intelligent from a player's perspective, while AI, on an industrial approach, for example, must focus on real-world problems [3]. But, since the '90s, when games evolve to be more complex, mixing different genres, it is possible to see the uses of genetic algorithms, neural networks, evolutionary approaches [4], and Deep Learning (a subset of Machine Learning) in video games, thereby decreasing the difference between AI and game AI. Nowadays game critics include the performance of AI in a game in the same way they assess its graphics, settings, physics, narrative, and more [5]. The Holy Grail for AI is to surpass the best human players in complex games such as StarCraft (Blizzard Entertainment, 1998), a sci-fi military-strategic game with intense resource management, where players assume three different roles using three different races. According to [6] the mastering of StarCraft is a challenge for artificial agents to compete and coordinate with other agents inside complex environments, so this game has emerged as a real target for artificial intelligence research. Since 1998, its release date, the StarCraft agents never come close to matching the best StarCraft players abilities, but in 2019 the StarCraft's agent AlphaStar surpasses 99,8% of the best human players in all 3 races of the game Protoss, Terrans, and Zergs, reaching a new milestone for the AI.

Despite the number of scientific papers related to this topic, and to the best of our knowledge, there is no bibliometric, scientometric, or informetric analysis of the existing scientific literature on the use of AI in video games. A search on Scopus and Web of Science (WoS) databases, with no proper results, seems to confirm that. Therefore, we intend to make a first contribution to filling this gap, by conducting a bibliometric study on the distribution and interest of publications relating to research between video games and AI, as well to identify the sources and authors with more scientific production. Thus, the research questions that this paper attempt to answer are the following: What are the most influential published articles? What are the main publication sources? Who are the most prolific authors from de search? What are the most frequently used keywords in articles published? To respond to these research questions, the major purpose of this study is to provide a holistic review of video games and AI research and to identify the challenges and gaps that are needed to be addressed by future research. The rest of the paper is structured as follows: first, the methodology used to obtain the dataset is described. Then, in Section 3, the results and quantitative analysis are presented, and finally, the discussion of the results and future work are addressed in Section 4.

2. Methodology

Before performing this search, topic keywords were applied to Scopus and WoS databases. As the Scopus took a significantly larger number than WoS, it was chosen. Our bibliometric analysis was carried out on publications published in peer-reviewed journals and conference proceedings; other documents such as books, reviews were excluded from this bibliometric analysis. Only publications written in English were considered, there were no time restrictions, and the search returned articles from 1971 to 2021. The resulting query is as follows:

```
(TITLE-ABS-KEY("computer game" OR "video game" OR videogame) AND TITLE-ABS-KEY("artificial intelligence")) AND (
LIMIT-TO ( DOCTYPE,"cp" ) OR LIMIT-TO ( DOCTYPE,"ar" ) ) AND ( LIMIT-TO ( LANGUAGE,"English" ))
```

A set of 2604 publications was returned. This data was then downloaded in RIS format. Later, this dataset was imported to the Biblioshiny for Bibliometrix in R 4.1.1. R is an open-source environment for statistical computing and graphics, with a collection of several packages such as Bibliometrix, developed specifically for bibliometric and scientometric studies [7]. Biblioshiny is a user-friendly web interface for Bibliometrix, to perform comprehensive science mapping analysis. Using those tools were carried out an analysis of a publication dataset and built matrices to perform network analysis for conceptual structure, intellectual structure, and social structure.

3. Analysis

Table 1 shows key information about data and document types retrieved from the Scopus database query on November 12, 2021. A total of 2604 publications from 1971 to 2022 were retrieved, of which 456 were journal articles, and 2148 articles from conference proceedings. A total of 5865 authors were identified, the average of authors per publication was 2.25 and 88% of the documents were written by more than one author.

Table 1. Main information about the search.

Description	Results
Total publications	2604
Articles	456
Proceedings papers	2148
Period	1971-2022
Date of query	12-10-2021
Authors	5864
Authors per document	2.25
Co-Authors per documents	3.19
Single-authored documents	351
Sources (Journals,proceedings)	810
Countries	77

3.1. Documents

The chart in Fig. 1(a) shows the growth of the number of publications published annually and the mean of total citations by year. The first publication returned was from 1971. Before 1999, the number of publications on AI and video games was on a slow-growth trend, ranging from 0 to 5. Starting from 1998, the number of publications has been increasing rapidly. Specifically, from 2004 to 2006 that duplicated the number of publications, and also between 2012 and 2016 the number of articles tripled, reaching its maximum of 316 publications in 2006. This trend is also consistent with the findings reported in other studies related to bibliometric analysis in the video games field [8] and [9]. But not in line with bibliometric analysis in the AI field ([10], [11]) where the biggest growth curve was in other periods. The underlying reason that video games and AI research has grown rapidly after 2004 could be attributed to the increase of interest in using AI solutions to solve classical problems of video games AI as pathfinding, decision making, strategy, and procedural generation [4].

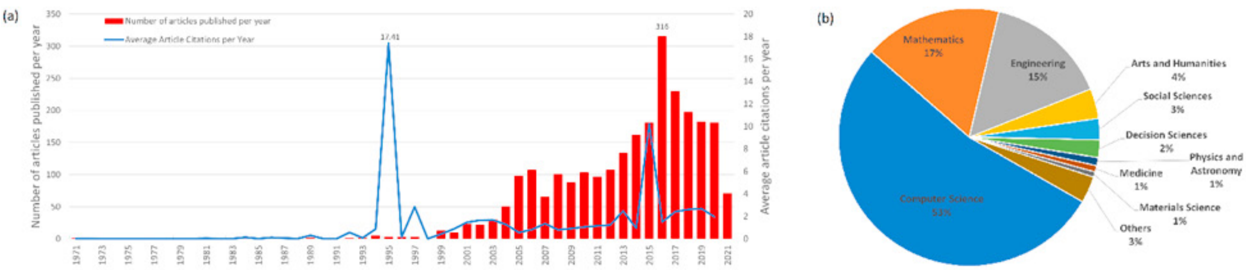


Fig. 1. (a) Annual Scientific Production and citation and (b) documents by subject area

In Fig. 1(a) it is possible to identify two citation peaks: the first in 1995 and the second in 2015. Two of the three works that the research returned this year contributed to the first peak ([12], [13]) with 847 and 527 citations respectively. For the peak of 2015, [14] contributed a lot with 8905 citations, completely distancing itself from the other publications this year. Looking at the graph in Fig. 1(b), it is clear that the most published field of research of Computer Sciences, followed by Mathematics and Engineering. This is no surprise given that video games and AI are inherently related to those fields. Table 2 shows the 10 most influential publications in video games in the AI field, based on the number of citations. As previously mentioned, [14] is the most cited publication with 8905 citations. The paper presents the first deep learning model capable of achieving the performance of a professional player in 49 games, having as input the pixels and the score of the game. In second place with 939 citations appears [15]. This publication unveils the smart technologies coded and used in Kinect for sensor calibration, human skeleton tracking, and facial expression tracking. With 833 citations, [12] presents the game-learning program using neural networks to play the game Gammon, coming in third place. In fourth position comes [16] with 654 citations. This paper presents the algorithm which would later defeat the best GO player in the world, and register one of the most important moments in the history of AI. In [13] is used the video game Tetris to study interactive processes of how agents configure their workplace for specific tasks and how they can continuously manage that workplace. In [17] the authors reflect on what is necessary for current AI systems to think like humans. For this, they review the progress of cognitive science and point out paths for what they learn and how they learn. In [6] a new breakthrough in AI and video games is announced, the multi-agent reinforcement learning algorithm (AlphaStar) is presented. After training, reaches the level of the grandmaster level in the real-time strategy game (StarCraft II), being able to beat 99.8 percent of all human players in the competition. In [18] cooperative algorithms based on the A* algorithm are provided that address specific cooperative pathfinding problems. [19] presents the algorithm for imperfect information settings adapted for games, where players have perfect information, and it was tested in a professional poker tournament. In [20] an algorithm based on the A* algorithm is presented, for finding paths in grids with locked and unlocked cells, used to represent 3D terrain in video games. Finally, [21] presents a program for playing poker, which uses learning techniques to build statistical models of each.

Table 2 - Most Global Cited Documents

Paper	DOI	Total Citations
MNIH V, 2015, NATURE	10.1038/nature14236	8905
HAN J, 2013, IEEE TRANS CYBERN	10.1109/TCYB.2013.2265378	939
TESAU C, 1995, COMMUN ACM	10.1145/203330.203343	833
SILVER D, 2018, SCI	10.1126/science.aar6404	654
KIRSH D, 1995, ARTIF INTELL	10.1016/0004-3702(94)00017-U	517
LAKE BM, 2017, BEHAV BRAIN SCI	10.1017/S0140525X16001837	502
VINYALS O, 2019, NATURE	10.1038/s41586-019-1724-z	437
SILVER D, 2005, PROC ART. INT. INTER. DIG. ENTERT. CONF., AIIDE	NA	291
MORAVČÍK M, 2017, SCIENCE	10.1126/science.aam6960	280
BILLINGS D, 2002, ARTIF INTELL	10.1016/S0004-3702(01)00130-8	191

3.2. Sources

Figure 2 shows an exaggerated concentration on few actors in Most Local Cited Sources, in which the first three sources account for 46% of the citations, while the other 7 share the rest.

Fig. 2. Top 10 most local cited sources

In Table 3 it is clear the predominance of two main sources. From the top ten publications, the first one alone holds 40%, and the first and the second together hold 58%. This also points to a preponderance of Bioinformatics, as the source that holds 41% of publications focuses on this area.

Table 3 - Top 10 sources and number of papers published during the period.

Sources	Number of papers
Lecture Notes In Computer Science (Including Subseries Lecture Notes In AI And In Bioinformatics)	417
AAAI Workshop - Technical report	183
Communications in computer and information science	80
IEEE Conference on Computational Intelligence and Games CIG	65
ACM International Conference Proceeding Series	58
IJCAI International Joint Conference on Artificial Intelligence	57
Proceedings of CGames 2005 - 7th International Conference on Computer Games	47
CEUR Workshop Proceedings	46
Advances in Intelligent Systems and Computing	45
Expert Systems With Applications	43

However, in Table 4, the Source Local Impact presents a more balanced distribution. Even with the first four places concentrating just over half of the local impact, the distribution is more homogeneous, considering the H-index, since the difference from first to last place is little more than double, 2.2x (20 vs 9), and not 9.7 times as much (471 vs 43) as in Most Relevant Sources. In the G-index this difference is greater, 3.5 times (45 vs 10) but it also maintains a more homogeneous distribution.

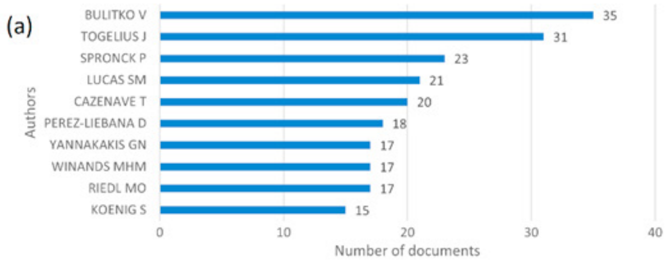
Table 4 - Top 10 most impact sources.

Element	h_index	g_index
IJCAI International Joint Conference On Artificial Intelligence	20	29
Lecture Notes In Computer Science (Including Subseries Lecture Notes In AI And In Bioinformatics)	20	31
Proceedings Of The National Conference On Artificial Intelligence	19	35
AAAI Workshop - Technical Report	15	28
IEEE Conference On Computational Intelligence And Games, CIG	13	25
Artificial Intelligence	12	13
IEEE Transactions On Cybernetics	12	14
IEEE Transactions On Computational Intelligence And AI In Games	11	26
2008 Ieee Symposium On Computational Intelligence And Games, CIG 2008	9	10
Proceedings Of The 4th Artificial Intelligence And Interactive Digital Entertainment Conference, AIIDE 2008	9	18

3.3. Authors

The documents analyzed were authored by 5864 different researchers, with an average of 0.444 documents per author. The large majority of those authors, 5555 (95%), produced documents in co-authorship, while 309 (5%) authors produced their documents without collaboration. There were 351 (13%) single-author documents.

Relatively to co-authorship indices, the Authors per Documents index is 2.25 and The Co-Authors per Documents is 3.19, the former being the ratio between the total number of authors and the total number of articles and the latter being the average number of co-authors per article. The collaboration index, that is, the ratio between the number of authors of multi-authored documents and the number of multi-authored documents is 2.47. Fig. 3(a) shows the most relevant authors per number of authored documents. The two most productive ones are Vadim Bulitko (University of Alberta, Canada) with 35 documents, an average of 2.5 per year published continuously from 2005 to 2019, and Julian Togelius (New York University, USA) with 31 documents, with the first publication happening only in 2014 but with an average of 3.875 documents a year since then. There are several measures used to quantify the impact of individual authors. The table in Fig. 3(b) shows the 10 authors with more local impact, by h-index. This is the most common measure used, although studies suggest that the use of the h-index in ranking scientists should be reconsidered [22].



(b)

Author	h-index	g-index	m-index	TC	NP	PY start
TOGELIUS J	13	25	1.625	649	27	2014
BURO M	12	13	0.667	429	13	2004
BULITKO V	11	20	0.647	446	31	2005
LUCAS SM	11	20	0.786	480	20	2008
PEREZ-LIEBANA D	10	15	1.429	376	15	2015
SPRONCK P	10	22	0.556	589	22	2004
YANNAKAKIS GN	10	16	0.625	442	16	2006
KOENIG S	9	11	0.5	520	11	2004
RIEDL MO	8	17	0.471	345	17	2005
MATEAS M	7	11	0.389	244	11	2004

Fig. 3. (a) The 10 most relevant authors by the number of documents; (b) The 10 most relevant authors by local impact.

3.4. Most Frequent Words

The analysis of the most cited words must be careful, due to the occurrence of synonyms and specializations. For example, the most cited term (Fig. 4), Artificial Intelligence, is a broad term that involves several specializations, such as machine learning, deep learning, and neural networks, which appear in 2nd, 14th, and 17th respectively. As for synonyms, Artificial Intelligence's abbreviation, AI, appears in 10th place, which would increase the initial count of 329 appearances for the keyword to 362, approximately 10% more. Regarding synonyms, we have the broad concept of digital games, which appears as computer games, or video games, usually, a difference in the hardware used, games, an abbreviation, computer game and video game, singular forms of the aforementioned plurals, serious game, a game genre, videogames, a synonym, and AI games and game design, digital games specialization areas. If added, these terms together come in at 427, that is, more than Artificial Intelligence and its abbreviation together (showing that these people know how to have fun). When used to analyze trends, as we will see later in Fig. 5, the separation of synonyms and technologies is important, as it allows us to observe how keywords evolve and become less general over the years, but when it comes to analyzing only the amount of words, without the need of a timeline, they can be put together without problems of interpretation.

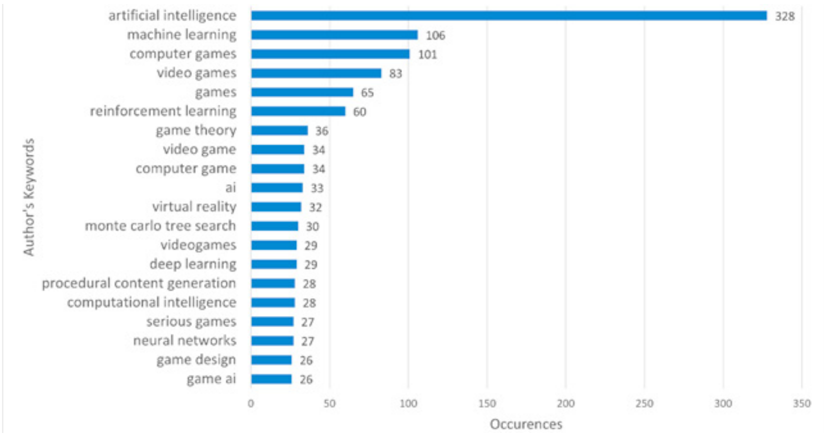


Fig. 4. Most relevant words by occurrences

Although the term Monte Carlo Tree Search (MCTS) first appeared in 2006 by Remí Coulom [23], it ends up standing out in 2016 when it is successfully combined with neural networks at work [16] and the era of deep learning is created. Procedural content generation in video games has a long history, but Fig. 5 shows that in recent years there has been an increase in interest around challenges posed by game content generation due to the emergence of deep learning tools. This search trend will likely remain a search for the foreseeable future.

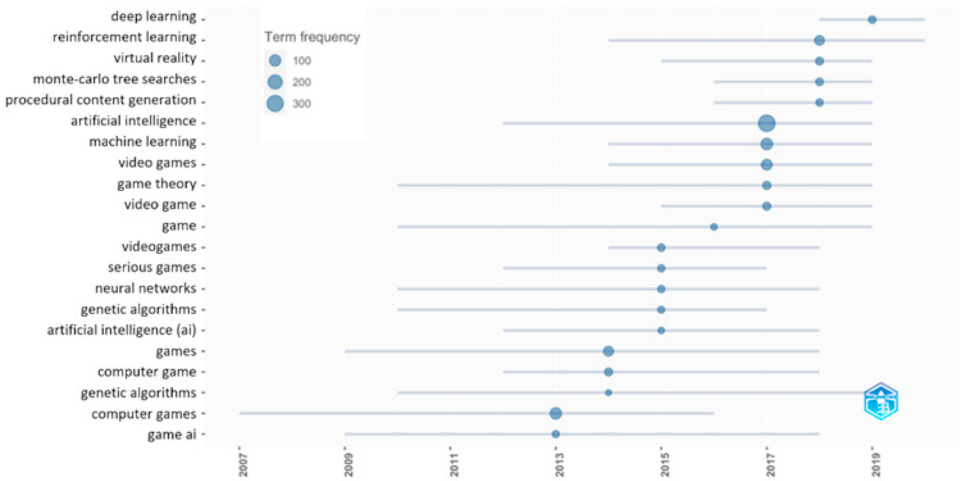


Fig. 5. Trend topics since 2007.

4. Discussion

Through the analysis of articles returned by the query, it was possible to identify two relationships between AI and video games: video games can use AI algorithms to incorporate into their gameplay. For example, the case of using an AI algorithm to create certain behaviors in an NPC, controlling the real-time strategy (RTS) game AI, or the procedural level generation. The use of video games to test and assess the ability of the algorithm to solve problems. Video games are usually designed to challenge humans and allow you to recreate more or less complex virtual environments. This makes video games excellent tools to test various cognitive problems, including reasoning, planning, strategy, coordination, perception, behavior, kinesthetics, among others. One example is the use of video games in learning algorithms ([6], [16], [19]). In the top 10 of the most cited articles, and through co-occurrence, it is possible to observe that researchers around the world are using video games to create environments to be used in learning algorithms. The doubling of the number of articles published in 2016, can be due to the convergence of some factors that promoted the rapid growth of deep learning, including the availability of a great amount of data and more processing power given by GPUs evolution, new algorithms like convolutional neural networks, in 2012, Generative Adversarial Networks, in 2014, and the availability of more user-friendly machine learning frameworks, like Tensorflow, introduced by Google in 2015.

Future work could deal with some shortcomings of this study: Incorporated other databases such as WoS, and others. To perform a screening strategy, analyze the content of the publication to verify if its focus is related to AI and videogames, and thus obtain a better sample. Lastly, considering the limitations of bibliometrics, a deeper content analysis of papers can be conducted to gain a deeper understanding of the AI and videogames relations.

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