Multi-Agent Systems on Virtual Games: A Systematic Mapping Study

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***Abstract*—*Context*: Games are a well-established scenario to test AI and Multi-Agent Systems (MAS) proposals due to their popularity and defiance. However, there is no big picture of the application of this technology to games, the evolution of the kind of problem tackled, or the game scenarios in which agents have been experimented.**
***Objective*: To perform a systematic mapping to characterise the state of the art in the field of MAS applied to virtual games and to identify trends, strengths, and gaps for further research.**
***Method*: A Systematic Mapping Study has been conducted to find primary studies in the field. A search was performed on title, abstracts, and keywords, whilst classification, data extraction, and further analysis were performed according to specific criteria focused on MAS papers with experimentation and evidence in a game scenario.**
***Results*: 78 studies published between 1998 and 2021 were found. Studies have been classified according to the MAS problem faced and the agent reasoning strategy. We detect that Machine Learning is the most common AI technique for MAS in games, considering both reinforcement learning and evolutionary techniques. MAS are used in a variety of gaming genres, especially in Real-Time Strategy (RTS), Sports and Simulation.**
***Conclusions*: RTS and Sports games are well-suited for concrete MAS problems such as multi-agent planning and task allocation. Expanding evidence and experimentation on other aspects related to scalability and usability issues is discussed. Those MAS problems and experiments that remain slightly modelled on games or are not thoroughly studied yet have been also identified.**

***Index Terms*—Multi-Agent Systems, Virtual Environments, Games, Systematic Mapping Study**

I. Introduction

In the last decade, the emergence and improvement of AI mechanisms have provided new opportunities to combine these novel techniques with Multi-Agent Systems (MAS), leading researchers to elicit and analyse the benefits, problems, and challenges of that combination.

MAS have been successfully applied in a wide range of domains such as industry, power systems, smart-grids, logistics, and video games or computer games, among others. The latter has risen as a growing field in industry [1], [2] and in Computer Science, where computer games have become an interesting scenario for AI training and testing. In a nutshell, games are considered interesting problems, difficult to solve, a rich scenario for human-computer interaction, and a great bank of data due to their popularity, among others [3]. Recent examples are Vinyals et al., who proposed a reinforcement learning MAS using deep neural networks to play Starcraft II [4] and Baker et al. with their proposal of developing a scale-based MAS competition to teach agents how to play hide-and-seek [5].

Notwithstanding the popularity of MAS in the Game AI field, there is no recent work that illustrates how this field is composed and evolved. Systematic Mapping Studies (SMS) emerge as a powerful tool to sketch and structure the state-of-the-art of a specific field in a broad manner. SMS have been widely used in different fields related to software and gamification [6], [7], [8]. The purpose of this paper is to conduct an SMS to provide a big picture of the state of the art of MAS on Games.

The main question to address in this study is the following: *How Multi-Agent Systems and Virtual Games are combined and applied in research?* To this end, we have decomposed this main question into a set of research questions:

- RQ1 What are the games and frameworks/tools used in the context of MAS?
- RQ2 What are the target publication sites/venues and their characteristics?
- RQ3 What are the predominant MAS algorithms used in games, and for what kind of games?
- RQ4 What are the MAS problems that are researched on games?
- RQ5 Which evaluation processes are conducted on the proposed MAS problems and algorithms?

This work aims to facilitate further research of both communities, to provide a mapping of the current work, identifying trends, strengths, gaps, and opportunities by analysing games and frameworks used to design the experiment scenario, venues of publication in which studies were published, algorithms and techniques used, problems solved, and evaluations used.

This paper is distributed as follows: Section II presents the SMS process. Section III details the results achieved given the research questions. Section IV discusses the results, problems, and borderline cases from the authors' perspective. Finally, Section V recapitulates the conclusions obtained based on the results obtained and presents the future lines in which this field has the potential to continue evolving.

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A. Background and Related Work

First of all, it should be started by setting a common understanding of what a '*game*' is. Zyda [9] explored the possible concepts of such a word, stating that people respond differently to the term 'game' depending on whether they played or did not play video games while growing up. This has been followed by in-depth research in the field from a perspective that goes beyond the playful objective, posing it as a means rather than an end. This ranges from well-known works such as Deterding et al. in their first attempt at defining Gamification [10], to much more extensive works that break down the basics, concepts, and techniques for both academia and industry. From their definitions, the following classification was described:

- **Game** is a physical or mental test with special rules. The aim is to entertain or reward the participant.
- **Video game** is a mental test using a software program. The aim is to entertain or reward the participant.
- **Serious game** is a mental test that uses the entertainment or reward of the participant for other purposes apart from fun, such as educating, learning, or health.

Although there is extensive research on MAS and games, so far there is no recent work that sketches a broad vision that combines both fields. In recent years, Yannakakis and Togelius published the *Artificial Intelligence and Games* book, where the Game AI field is introduced, including extensive documentation of how to integrate AI methods into Games, with special emphasis on machine learning and content generation techniques [3]. Their work is a comprehensive guidebook for Game AI students, researchers, and programmers that includes concrete mentions of MAS in AI research.

Related to the study of the state-of-the-art of agents and games, Yildirim et al. analysed certain aspects such as autonomy, reactivity, and goal-oriented behaviour from different Non-Playable Characters (NPCs) in a set of games as intelligent agents [11]. Their work is a profound research on investigating whether it is possible to view NPCs in games as goal-based agents focusing their evaluation on a representative set of popular commercial games, and also provides a survey on the use of various AI methodologies in both academia and industry. In contrast to this work, we want to discover which are the games that apply agents within a MAS context, as well as to discover which have been the different designs, algorithms, and techniques on the agents that compose them.

Hocine and Gouaich analysed the principal studies facing the adaptation problem on serious games from the perspective of the agent behaviour modelling [12]. Moreover, Beal et al. surveyed the state of the art of machine learning techniques in team sport games [13].

II. Method

Taking into account the previous section, the main question to be addressed in this study is: *How Multi-Agent Systems and Virtual Games are combined and applied in research?* To do so, the SMS guidelines from Petersen et al., focused on Software Engineering [14], [15], has been followed. The intention is to study the state-of-the-art that converges MAS and Game experimentation approaches. With this study, our objective is to map the field through this approach, identify trends and gaps, extract some 'de facto' decisions or conventions, discuss the results, and propose some future lines. With that aim, we first extracted the RQs introduced above from the main question, and then applied the adapted SMS process to our meta-study. The motivation for this breakdown of questions is, in essence, to sketch a first picture of how research combining the two fields of study related to games and MAS has been developed and evolved. Each of the questions allows us to know first place-specific aspects of the corpus obtained: which game genres and tools involved have been used, which have been the most relevant venues of publication and their scopes/topics where studies have been found applications over time, which algorithms and MAS techniques have been designed, and which have been the evaluations carried out to obtain the relevant evidence.

The following subsections describe the search process, summarised in figure 1.

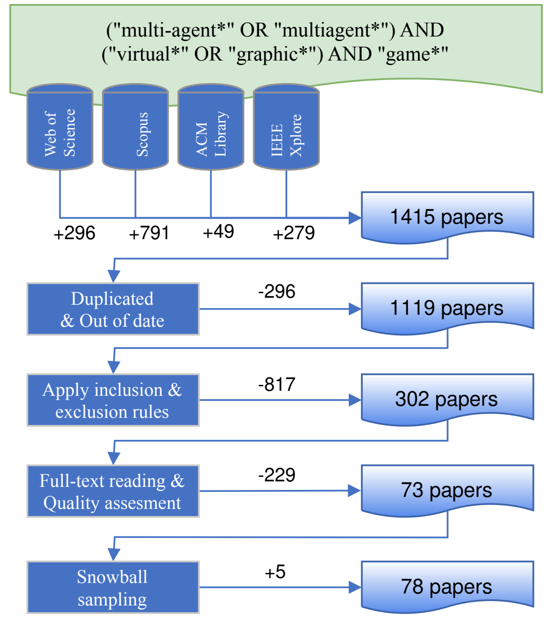

Fig. 1. Search process.

A. Search strategy

The search protocol was designed according to the suggestions from [15]. The search was developed and reviewed by different authors. A *PICO* search strategy was defined to identify keywords and formulate the search string extracted from RQs:

- **P**opulation: Studies and proposals that include MAS in their proposal.
- **I**ntervention: Experiments based on a virtual game scenario.
- **C**omparison: Contrast of the different MAS-based proposals with proposed game scenarios.
- **O**utcome: Not defined, because the aim is to analyse the obtained outcome.

The main extracted keywords are *multi-agent* and *virtual game*, being aware of the lack of consensus in the terminology caused by their evolution over time. The variations from a preliminary literature review to make the search more flexible were included. In addition, extensively well-known keywords such as *experimentation* or *scenario* were obviated. The search strings and candidate repositories were iteratively refined until the last obtained corpus was stable according to an inter-rate agreement. Figure 1 includes the final query string and selected repositories, and includes the number of papers obtained per repository. RefWorks ProQuest[1] was used as a reference management tool to remove papers based on abstract-based exclusion criteria.

B. Study selection

Articles were excluded in two phases. In the first phase, exclusion was applied based on titles, keywords, and abstracts. In the second phase, works were excluded based on full-text reading and quality assessment. Studies have also been added by backward snowball sampling.

The following inclusion criteria were applied:

- Studies in the field of CS and MAS.
- Online studies published up to and including 2021.
- Studies that include experimentation.
- Studies that describe a virtual scenario with gamified elements.

The following exclusion criteria were applied:

- Short papers (5 pages or less).
- Studies not presented in English.
- Non-accessible full-text papers.
- Books and gray literature.
- Duplicates.
- Non-peer reviewed.

Each article was evaluated through a grading methodology. Each paper received independent grades from three authors of the present study, namely A if accepted, B if doubt, or C if rejected. Each grade attaches a value (A=1, B=0, C=-1). Only papers with a total grade of 1 or higher were selected as members of the final corpus.

C. Quality assessment

In order to reduce biases, the inclusion and exclusion criteria labour were conducted in parallel by three of the authors separately. Furthermore, a quality assessment phase for the studies was defined, excluding those papers that fail to answer one or more of the following questions according to the majority of the authors.

- *Is the motivation and problem of the paper clearly stated?*
- *Is the game scenario clearly defined and well contextualised with the study?*
- *Does there exist empirical experimentation involving the game scenario?*
- *Are there empirical evidence and discussion/conclusions from the results?*

[1]https://refworks.proquest.com/

TABLE I
DATA EXTRACTION FORM.

Field	Description	RQs
General		
Title	Article name	
Id	RefWorks Id	
Authors	Set of authors names	
Year	Year of the study publication	2
Venue		
Name	Publication venue name	2
Type	Type of the venue	2
Topic/Area	Knowledge area of the venue	2
Proposal		
Problem	Description of the problem	1, 4, 5
Family	Agent reasoning method	3, 5
Algorithm	Name of the MAS proposal	
Scenario		
Name	Name of the game	
Rules	Game description	1
Development	Language/Framework/tool for experiments	1
Genre	Game genre	1, 3, 4
Commercial	boolean	1, 4
Experiment	Experimentation description	5

These questions pretend to assess the primary studies in aspects such as the motivation of the studies and how the game proposal is integrated into the experimentation, and the real purpose of the game in the study. In summary, the aim is to discard those papers that are not correctly contextualised into the problem. It is important to note that these questions aim to identify and include both studies on 'just for fun' games and serious games, separating those studies that propose a game scenario from just a virtual environment with few gamified elements but do not construct a gaming experience.

D. Classification

The articles were classified into different categories according to the proposed research questions. Then, data extraction from the studies was split among three authors and reviewed by the other for correctness and accuracy. Table I summarises the form used for data extraction and keywording from selected papers and the attached RQs.

- *General*: Basic information from papers.
- *Venue*: Mainly related to RQ2, includes publication-related information from the studies.
- *Proposal*: This category includes related information on the application of MAS in selected studies.
- *Scenario*: This field was designed to obtain the main relevant information from the scenario and the experimentation, including the game assets and design of view.

III. Results

The scope of this paper is to provide an empirical analysis of the SMS using the RQs explained in Section II. Figure 7 summarises the paper classification according to the exposed RQs:

A. Games and Tools (RQ1)

Depending on the playability of a game, it can be classified in different ways. This classification is called **game genre**, inspired and extended by Yannakakis and Togelius [3]. Figure 2 shows the different classifications made in this work based on the games analysed and the most used game genres. Games may be classified into the following genres:

1) Shoot'em Up: Games in which the player must shoot his way through large waves of AI enemies. Traditionally, these games are set in air or space battles in a fast-paced environment [16], [17].

2) Real-Time Strategy (RTS): Subgenre of strategy in which the player, normally in the role of leader or general, must manage his resources and forces in real-time to win an AI or other players [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33].

3) Puzzle: Also known as logic games, they pose a mental challenge to the player that must be solved [34], [35].

4) Sports: Virtual and interactive simulation of a sport such as football or basketball. Other types of game simulation have been included within this category, such as Capture the Flag or Catch the Prey [34], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47].

5) First Person Shooter (FPS): Games in which the player, taking a first-person role, must face other enemies (AI or players) armed with different shooting weapons [34], [48], [49], [50], [51], [52], [53], [54], [55].

6) Education: Games for primarily educational purposes. In contrast to other serious games, educational games are considered games whose mechanics are more focused on learning than on a game attributed to another genre [56], [57].

7) Quiz: Games of questions and answers, in which one or more players earn points based on their answers [58].

8) Simulation: Games that seek to imitate some area of real life giving primary attention to realism [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74].

9) Maze: Games in which the player or the players must go through a maze to earn points or reach a specific point [34], [75], [76].

10) Turn-Based Strategy (TBS): Subgenre of strategy in which the action takes place in discrete events of time and, as in RTS, the player must plan and manage their resources to defeat the AI or other players [77], [78].

11) Storytelling: Interactive stories in which the player decides the characters' actions to advance in the adventure [79], [80], [81], [82].

12) Role-Playing Game (RPG): Games in which one or more players assume the role of characters in a generally fictional setting that they can explore. Both the characters stories and their abilities and powers are normally developed during the game [83], [84], [85], [86].

13) Massively Multiplayer Online Role-Playing Game (MMORPG): Games that share the properties of the RPG but take place in a multiplayer world to which a very high number of players have access simultaneously, being able to interact with each other and with the environment [87], [88], [89], [90].

14) Multiplayer Online Battle Arena (MOBA): Multiplayer subgenre of RTS in which the player takes the role of a hero within a team and must face the opposing team to defeat their heroes and defences [87].

15) Fighting: Games in which players choose a character and combat with other characters in a close scenario [91].

16) Racing: Games based on driving competition between players or against the AI [34].

17) Platforms: Games in which the player travels through different scenarios, usually jumping or climbing, to reach the goal [34].

18) Board game: Virtual simulation of a board or tabletop game. Usually, these types of games tend to be multiplayer and turn-based [92], [93].

It should be noted that games in several of the selected publications were defined as serious games. Although this category is not related to a single genre, in the calculation of our study, they represent 16% of the total, with 12% corresponding to the Simulation genre [59], [60], [62], [63], [64], [65], [66], [71], [73], and 4% to Education [56], [57], [74].

Regarding tools and frameworks, a relevant fact is that most of these publications do not base their experiments on commercial games but rather build their scenarios, taking other existing games as a reference. That is why a great variety of additional tools and frameworks are used to define the behaviour of the agents and to build scenarios and experimentation environments.

Figure 3 shows the types of framework that have been differentiated, which are the following:

1) Game/Physics Engine: Game and physics engines are software specialised in 2D or 3D rendering and provide easy tools for physics simulation and collision detection, animation, graphic scenarios, etc. [18], [19], [20], [22], [24], [27], [28], [38], [43], [45], [47], [48], [52], [54], [57], [59], [60], [62], [63], [67], [69], [72], [73], [88], [90], [91].

2) Virtual Framework: This category includes publications working with tools that provide a virtual 2D/3D environment without the majority of the features that the Game/Physics Engine has. [21], [30], [31], [34], [42], [68], [71], [83].

3) Pure code: The articles classified here use code without any visual interface [16], [23], [25], [32], [33], [35], [39], [40], [49], [50], [51], [53], [55], [58], [64], [65], [66], [74], [76], [80], [81], [82], [84], [85], [89], [92], [93].

4) N/A: Articles classified as *non-available* are those that have only a mathematical demonstration, pseudocode or do not provide any information. [17], [26], [29], [36], [37], [41], [44], [46], [56], [61], [70], [75], [77], [78], [79], [86], [87].

Although the most popular Game Engines, such as Unity3D or Unreal Engine, are quite widespread, we have evidenced a great heterogeneity in the use of tools and frameworks according to the needs of the problem and the game scenario to be modelled. The popularity of JADE as a middleware used to code the behaviour of agents is also noteworthy[2], but it should be highlighted that this tool is exclusively a multi-agent framework on which the game scenario is supported, whether it is a game engine or another virtual framework.

[2]https://jade.tilab.com/

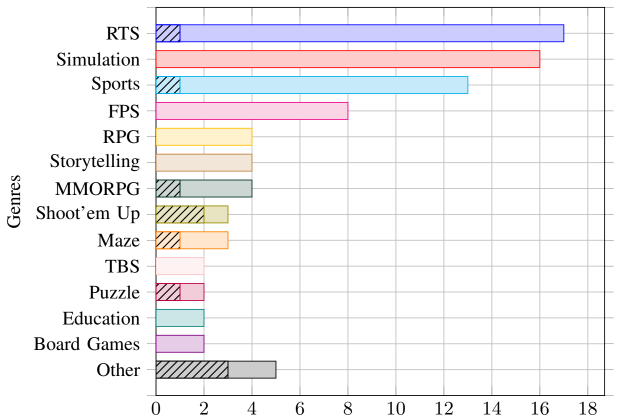

Fig. 2. Game genres chart. Lined bars refers to studies with multiple games.

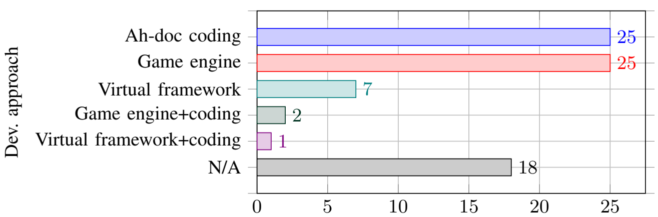

Fig. 3. Tools and frameworks used.

B. Venues of publication (RQ2)

The motivation for this question arises to understand the trends in the publication of the studies included in this meta-study. Answering this question allows us to identify the source of publication of the studies, their type, topics, and scope over time. Figure 4 shows the number of publications of interest for this study from 1998 to 2021. As far as it was identified, the first article relevant to our study was published in 1998, but it was not until 2006 that the publication of the included papers became more normalised.

Figure 5 summarises the trend in the venues and types of publication considered, whereas Figure 6 summarises the topics of such venues. In a nutshell, studies were mainly published at IEEE and ACM conferences and corresponding proceedings over time. 28% of the studies were published in journals, while 72% were published in conferences, the most

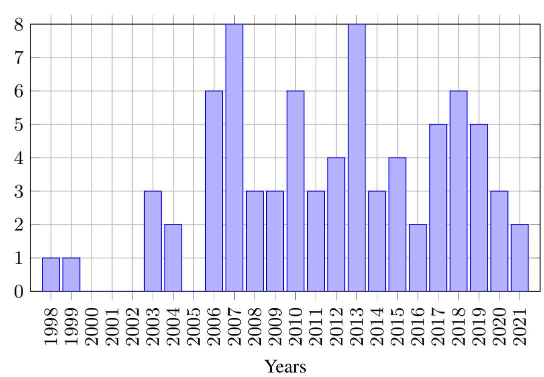

Fig. 4. Publications per year.

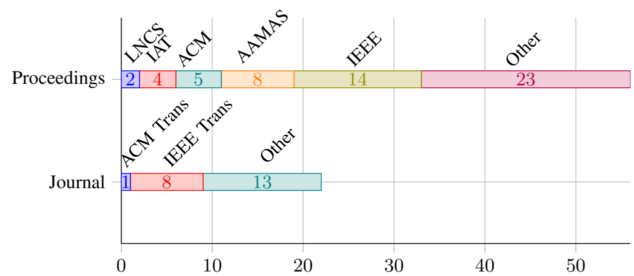

Fig. 5. Venue types.

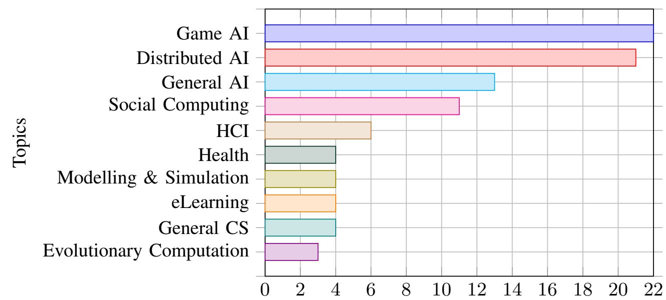

Fig. 6. Topics (there are venues that are part of several categories).

relevant being the AAMAS conference and IEEE Transactions on Games, representing 10% of the accepted papers. 'Other' publications are composed of a wide variety of venues, such as specialised workshops and conferences focused on general and distributed AI, among others. The most frequent topics, regardless of the type of venue, are Game AI (28%), Distributed AI (27%), and General AI (17%). The first category encompasses the different journals and conferences focused on intelligent systems applied to video games (dominated by IEEE CoG and ToG, formerly named CIG and T-CIAIG, respectively). The second category covers venues of distributed and intelligent systems with autonomous agents (e.g., AAMAS, ICAART, IAT). The topic General AI comprises a variety of general-purpose venues within the framework of Artificial Intelligence.

C. Algorithms and Game scenario (RQ3)

Our classification of MAS proposals was based on the agent reasoning architecture inspired by the classical reactive/deliberative/hybrid topologies from Wooldridge [94] and the classification of agents from the survey by Hocine et al. [12]. Due to the heterogeneity of Agent-oriented development, agents may be composed of different reactive or deliberative processes based on their perceptions and actions. It is important to note that this classification is based on the predominant technique(s) in the accepted papers. According to it, the different proposals from the selected papers were identified and grouped according to the following criteria:

1) Belief-Desire-Intention (BDI) agents: Deliberative agents in which their actions (intentions) are selected based on the perception of the world (belief) and the goals (desires) to be achieved [16], [35], [48], [49], [50], [51], [53], [54], [59], [66], [69], [79], [81], [88]. The studies identified in this category are mostly characterised by deliberative strategies in conjunction with the sensor-cognition-action cycle, which integrates the sensing process with the reasoning and execution of beliefs, plans, and actions. [16], [35], [49], [50], [51], [69], [79], [81]. In a nutshell, during the sensor/perception process, agents acquire, filter, abstract, and conform beliefs from sensed data, the action process controls the execution of external acts on effectors upon their environment, and the cognition process is aimed at interpreting such perception and performing a plan involving perceptions and beliefs to solve the problem. The most widespread motivation for the use of this paradigm, although varied, is the simulation of social, deliberative, and/or reactive processes with incomplete information, given its similarity to mental processes from psychology.

2) Rule-based agents: Agents whose behaviour, knowledge, and deliberations are mainly based on rules [22], [24], [26], [28], [38], [40], [41], [43], [45], [58], [62], [63], [67], [71], [81], [84], [87], [92]. This category comprises a diverse variety of proposals. From the perspective of modelling agents' knowledge and behaviours, techniques such as math-based rule definitions and constraints as satisfaction/optimisation problems [24], [26], [38], [41], [81], [87] and ontological representations with formal logic-based expressions [40], [58], [84], [92] stand out. Synthesising, both are focused on defining decision problems whose solutions involve finding a plan or a set of decisions from agents as the assignment of the variables they individually control (boolean and/or arithmetic) on a set of constraints applied to them. To a lesser extent, we can highlight the use of behaviour trees (a tree of hierarchical nodes that control the flow of decision-making of an agent) [28], [84], a popular approach for non-player characters in the game industry.

3) Automata (FSM) agents: Agents are modelled as finite-state machines, deterministic or not, in which agents traverse a set of actions depending on their state and specific triggers, generally inspired by models of simple and repetitive human and social behaviours [19], [27], [46], [54], [60], [64], [72], [86].

4) Inference-based agents: Agents with an inference mechanism in which their decisions are inferred following logic and/or probabilistic knowledge, resulting in a degree of belief in their facts and plans [17], [27], [34], [37], [46], [56], [68], [80], [82]. Proposals are mainly modelled through the Markov Decision Process (MDP) framework. MDP models agents through a discrete-time stochastic control scenario to find a plan (namely a policy) based on collected outcomes that depend on modelled random effects provoked by agent decisions. This mathematical framework is used in different extensions and generalisations, such as Hidden MDPs, and Partial Observable MDPs, where the agents cannot observe all the conditions of the scenario, either some of its states or parameters that influence it, respectively [27], [37], [56], [68], [80], [82]. These variants are used to characterise a certain degree of uncertainty over the knowledge, perceptions, and actions of the agent. Other approaches included implementing Bayesian networks [56], influence diagrams [17], and fuzzy systems [46].

5) Reinforcement Learning (RL-based) agents: Agents based on training techniques based on actions to build behaviours based on policies that maximise their cumulative reward [29], [31], [32], [33], [34], [36], [42], [47], [55], [57], [65], [73], [77], [85], [89], [90], [91], [93]. Within this category, the most commonly used techniques are mainly the following:

- Q-learning: agents are aimed at shaping a policy by learning the values of controlling variables attached to their actions given a particular internal state. To do so, agents explore their state map (commonly known as an MDP or variant) by transiting over the different states through pseudo-random actions to maximise the total reward (the Q-value) [29], [31], [36], [55], [65], [89].
- Deep Reinforcement Learning: agents that combine RL and Deep Learning techniques, the latter consisting of neural networks and their composition in different structures (multi-layer/deep, convolutional, adversarial, etc.). In this subgroup, there is a wide range of proposals, such as Deep Q-learning (DQN, a variant of Q-learning that uses neural networks to approximate the Q-value) [31], [32], [47], [51], [55] and algorithms based on gradient descent policy search (iterative optimisation to find the local minimum of a differentiable function), such as Proximal Policy Optimisation (PPO) [47], [73] and Asynchronous Advantage Actor Critic (A3C) [55], among others.
- Episodic learning using Monte-Carlo methods: agents learn from the sampled experience by averaging values from states in all the iterative episodes sampled. The values of the variables controlled by the agents are updated after each completed iteration [29], [34], [90].

Interestingly, most of these algorithms are model-free, where proposals are not attached to stochastic distributions over transitions and rewards typically associated with MDPs, such as DQN, A3C, PPO, and Monte-Carlo. This property characterises a trial-and-error approach that allows these algorithms to rely on real samples from the environment, avoiding generated predictions from the next state/reward to select or modify agent behaviours (although they might sample from experience memory, which is close to being a model).

6) Heuristic-based agents: Techniques for solving MAS problems that employ a practical method that is not guaranteed to be optimal but is sufficient to achieve a solution or approximation in a reasonable time [18], [20], [21], [23], [25], [30], [34], [38], [39], [44], [52], [61], [69], [70], [74], [75], [76], [78], [83], [84]. This category is dominated by proposals based on evolutionary computation, with the objective of training agents to plan and select the most productive behaviours and/or those that minimise their effort and communication. Within this subset, we find different approaches such as genetic algorithms for agent survival and/or reproducing training [25], [61], [69], [70], other evolutionary algorithms for agent planning such as sequences of actions [30], [34], [75], [76], [84], and Neuroevolution that combines the latter approach with neural networks [23], [44], [75], [78], [83]. In addition, we have found proposals based on multi-agent potential fields for motion planning. Inspired by physical fields that obey

Laplace's equation (such as electrical, magnetic, and gravitational fields), a potential-field algorithm uses this paradigm to teach agents to move around in a certain space to reach the target point and avoid obstacles by using repulsive/attractive surfaces and vectors [18], [20].

These last three categories represent the papers whose agents in their MAS include machine learning techniques. Although heuristic-based methods are not necessarily associated with ML techniques, articles classified in this field are strongly geared toward evolutionary/genetic algorithms for agent behaviour planning, with a concrete mention of the potential field technique in RTS games for motion planning [18], [20]. Machine learning and rule-based techniques were used in most game scenarios, being RTS, Sports, and Simulation games the most popular. In fact, as the literature has progressed, deep RL-based techniques have become more popular, either by implementing their own *ad-hoc* MAS incorporating neural networks within the agents or, more recently, by using frameworks such as Unity's ML-agents[3] that provide the entire deep training infrastructure directly within the game engine [57], [90], which includes several of the deep algorithms proposed from accepted papers in this category.

In any case, several papers perform a combination of different algorithms from different categories. Generally, these studies usually combine a learning-based technique with a non-learning technique to reinforce the strategy and behaviours that depend on the latter. This includes proposals that combine heuristic techniques with rules (such as constraints or logical expressions) through optimisation problems [38], [84], sensing agents with evolutionary behaviours [69], or automata agents that apply swarm intelligence-based algorithms to find policies on their inner FMS [27]. In the GVGAI Competition, several candidates combine Monte Carlo learning with evolutionary strategies [34]. In [81], sensing agents combine a joint planner architecture composed of a set of rules to model the decision variables and their constraints (from Constrained Satisfaction Problems or CSPs) with BDI and deliberative techniques to perceive the environment. [46] combines episodic memory in individual agents and a logic engine to calculate the best strategy based on symbolic information from neighbours for deliberative actions.

The upper left green quadrant of Figure 7 relates the algorithms and techniques described in agents to the genres of games being experimented with. From a game perspective, the Sports genre offers a suitable scenario for MAS proposals, regardless of the technique, football being the most representative with virtualised versions of competitions such as RoboCup League or Robot Soccer [36], [37], [38], [41], [42], [43]. Simulation games also show this trend, according to the real-life aspect aimed at studying and representing. It is interesting to mention the use of BDI modelling for FPS games. BDI-agents deliberate based on well-known but soft goals in these games (survive, reach location, destroy enemies, etc.). In fact, these deliberative agents must act based on the perception of the world rather than on reactive stimulus, assuming incomplete, outdated or even incorrect information in some cases [48], [49], [50], [51], [53], [54]. (Deep) learning and evolutionary algorithms are mainly applied to different 2D games [34], [75], [76], [77], [83] and RTS games [21], [30] or 3D with an isometric perspective that can be abstracted from the interaction of a 2D game such as Starcraft [32], [33], [38].

It was found that the study of collaborative/competitive agents is included in the literature in a cross-cutting manner, where such interaction is determined through the game and scenario rules. In general, this aspect tends to be a precondition and is generally relegated to the sideline. Sports and RTS papers are good examples of how agent reasoning and other questions are studied over the condition of agent cooperation (as a team) and competition (team vs. team).

D. Problems on Games (RQ4)

Related data were extracted and classified according to the taxonomy for MAS applications and problems of Dorri et al. [95] and incorporated a category extension.

1) Agent modelling: Include studies aimed at defining and modelling agents related to the problem or scenario. In fact, this category includes agent-based framework proposals and agent descriptions [35], [48], [54], [55], [58], [63], [69], [71], [84], [92].

2) Team formation: The problem consists of finding the best subset or coalition of agents to achieve a common objective, and maintaining team cohesion in the presence of a common problem [16], [32].

3) Agent planning: Completion of joint strategies or action sequences [16], [17], [18], [19], [21], [23], [24], [27], [28], [29], [31], [34], [37], [38], [39], [40], [42], [43], [44], [45], [46], [48], [50], [52], [55], [61], [62], [64], [67], [73], [76], [77], [78], [79], [80], [81], [83].

4) Task(resource) allocation: Consists of the assignment of tasks or resources among agents [22], [25], [36], [40], [41], [49], [53], [65], [91].

5) Behaviour adaptation: Problem category in which agents aim to react and respond to some degree. In other words, agents are expected to evolve according to the scenario [28], [30], [33], [47], [85], [87], [89].

6) Path-finding: The problem is to find paths for multiple agents so that each agent reaches its goal and can manage collision risks [18], [19], [22], [26], [32], [72], [76], [88].

7) Performance: Problems related to improving MAS performance, such as runtime execution, scalability, and communication, among others [53].

8) Human-AI (HAI) interaction: Problems related to user integration into the system through interaction with virtual entities as agents [20], [45], [56], [57], [59], [60], [63], [66], [67], [68], [74], [82], [83], [86], [90], [93].

9) User training and user engagement: Problem category based on user traits, such as satisfaction and learning [51], [59], [60], [71], [73], [74], [75].

10) Social simulation: Studies focused on problems related to the modelling and simulation of social phenomena [70], [71], [90].

[3]https://github.com/Unity-Technologies/ml-agents

Analysing the most popular genres in Figure 7 (upper-right red quadrant) based on the MAS problems can be concluded that RTS are mainly used to solve problems about agent planning such as attack and defensive behaviour and problems about path-finding. Simulation games are mainly used to research agent planning (in this case, to simulate behaviours) and HAI interaction. Sport games are used mainly in agent planning research to develop and coordinate team play.

As can be seen, in all these cases, the agent planning study is the most popular area of research, and is also used more often in the most common genres (RTS, Sports, Simulation and FPS). Nevertheless, HAI Interaction (especially in Simulation Games) and Task Allocation are also popular areas of interest.

Certain MAS scenarios are quite cross-cutting to pose various problems. From our understanding, these scenarios focus more on being able to represent dynamics linked to specific games than on solving the problem per se. We highlight the design of populous agent systems to represent dynamics such as crowds [59], swarms [25], [27], and predator-prey behaviours [75], among others.

On the other hand, although certain well known MAS problems are relevant for the Game AI and MAS communities separately, their presence in the selected studies is anecdotal or practically nonexistent. For example, Coalition structure generation is a subset of Team formation problems, where the set of agents is partitioned into mutually disjoint coalitions so that the total reward of the resulting coalitions is maximised [96]. RTS games such as Starcraft or Total War series, for example, allow the user to assign a hotkey to group a selected subset of units (usually, control+{1-9} key combination) to facilitate the command of a large and diverse set of units with different purposes during play. Coalition problems may be considered to conform suitable groups to support players or AI given concrete criteria. Indeed, team formation problems are suitable in these scenarios where agent planning and task allocation have been addressed so that agents may conform subteams to hierarchise and/or subdivide before facing the main problem. This may be considered in Sports, RTS or Simulation games with a large set of collaborative agents with different roles or purposes. For RTS games, collaboration as effective coordination actions has been identified as one of the six main challenges in the Buro vision paper of 2003 [97] that initiated AI research on RTS games. All these challenges, but collaboration, have had extensive work and publications.

E. Evaluation and Evidences (RQ5)

Studies were identified and grouped into categories based on the experimentation process and the evidence shown. Like in previous research questions, these works may have been performed one or more evaluations from different categories.

1) Performance: Experiments focused on analysing different runtime algorithm properties [22], [31], [35], [37], [41], [42], [61], [65], [66], [75].

2) Use(test) cases: Experimentation was conducted on the application of the algorithm or method under different conditions or parameters over the scenario [17], [18], [19], [20], [22], [23], [25], [27], [28], [29], [30], [32], [34], [35], [36], [37], [40], [41], [44], [45], [48], [49], [50], [54], [56], [57], [58], [59], [60], [63], [64], [66], [67], [68], [70], [72], [73], [75], [76], [77], [78], [80], [81], [82], [83], [85], [86], [87], [89], [90], [91], [92].

3) Comparison: Experimentation is based on the comparison between different methods, techniques or technologies [16], [17], [18], [19], [21], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [36], [38], [39], [42], [43], [46], [47], [49], [53], [55], [61], [65], [67], [68], [69], [73], [76], [77], [79], [80], [84], [85], [87], [88], [89], [93].

4) User satisfaction: : Evaluation of user comfort and acceptability during system interaction [22], [45], [66], [71], [75], [82].

5) Usability: Evaluation is based on the analysis of the ease of the system being tested by real users [52], [62], [74].

6) Scalability: Experimentation to determine how resources and runtime grow as the problem increases [42], [81].

Within the corpus obtained, a set of accepted papers perform experimentation using different techniques for experimentation, usually with algorithms within the same category. This is especially evident in studies focused on ML agents that mainly compare their fitness and strategies within the game as competitions [34], [47], [55].

It should be noted that user satisfaction and usability are related to User Experience (UX), but focused on different objectives. User satisfaction seeks to obtain a personal evaluation of the experiences and impressions of users, whilst usability studies refer to those who seek to perform an analysis on the effectiveness, efficiency and validity of design and interaction decisions.

A set of weaknesses and shortcomings related to these UX evaluation processes were found. Certain satisfaction test conducted with users possess a reduced number of participants for the context proposed: around 8-14, except for [82] with a set of 240 participants. Papers with usability tests have problems: only [62] provides the number of participants (5) and conducts tests based on a standard System Usability Scale questionnaire. It was concluded that experimentation in this area offers poor results and little impact. We evidence that papers scoped on HAI interaction and user training/serious games do not focus on these evaluations. Although these studies raise questions focused on the user (motivation, fun, learning, etc.), important aspects of the user experience are not evaluated in a deeply or systematically, such as satisfaction, interaction design, memorability, user safety, and efficiency, among others. These types of evaluations allow the extraction of results that can relate to the impact of the AI on the user within the game. For example, to properly analyse the increase of user comfort threshold or engagement when interacting with multiple agents.

Fig. 7. Bubble plot summarising the classification. Bars correspond to the number of papers labelled according to the classification from research questions (the joint sum of bars and bubbles can exceed the total number of papers, since there are studies that are part of several categories).

The evidence from a perspective of MAS scalability on games is marginal. Most of the works focus on the effectiveness and validation of the proposed hypothesis, but in a constrained scenario in terms of a growing number of agents. As explained in Subsection III.C, the game and its rules impose such constraints, but considering these modifications makes it possible to observe and analyse new behaviours of the agents in the experiments and extract results that make it possible to transfer the solution to other similar scenarios and games. For example, this applies to sports-based games, from futsal with ten agents (five per team) to other possible simulations with more players, such as rugby with 30 players. RTS and FPS games can also benefit from this type of evaluation, extrapolating the solutions proposed in these games with different magnitudes of units/players to be managed. In fact, for those MAS scenarios that involve solving high-complexity problems (NP-hard and larger), the study of the scalability of the proposed solution is a generally important aspect to consider.

As described in the lower-left blue quadrant of Figure 7, the predominant experimentation is based on test cases and comparisons. It was observed that the selection of one, another, or both types of experimentation is dependent on the existence of a predecessor or previous proposal to be compared. Otherwise, greedy, fixed, or random strategies are used for base comparison [36], [65], [77]. In the same way, several RL-based methods were compared with non-learning agents [42], [65], while evidence on evolutionary algorithms is obtained from tests and self-comparing of different setups from the game scenario and/or (meta)parameters [25], [30], [44]. Furthermore, the lower-right orange quadrant from Figure 7 shows how agent planning, followed by HAI, task allocation, and modelling papers are the most predominant over the MAS problem set for these two main evaluations.

Finally, almost no studies focus on scalability, so there is no concluding evidence on large-scale MAS on games. Similarly, although several HAI papers were identified, user satisfaction nor usability experimentation were not considered, so the evidence in these approaches is also weak. This implies a gap in the way this field is studied due to the focus on the reasoning of agents with users but a lack of more experiments and results with respect to their interaction design.

IV. Discussion

In this section, the most relevant results obtained are discussed, along with possible biases and flaws during this study.

A. *Game genres and popularity*

The study of the analysed video game genres shows a discrepancy between the commercial popularity of games and their scientific use [98]. This is especially striking in genres such as MMORPG and MOBA, which are quite popular in the game industry, and yet very few publications have been found concretely on MAS. This may support the argument that certain genres are more suitable than others to be considered in MAS studies for distributed AI-focused research. In any case, this should not be a strong restriction, since the consideration of the use of distributed agent systems ultimately depends on the suitability of the game design and its specific characteristics (scenario, interaction, players, rules, goals, etc.).

Regarding the genres of the studied works, Simulation, RTS and Sport are the most popular ones. This may be because these genres, especially the last two, share many similarities with MAS, such as team structure and dynamics, planning, and resource management and coordination. The attractiveness of these genres to be modelled through MAS is evident. Moreover, the competitive nature of these genres makes them especially suitable for confronting agent teams with different strategies or problem modelling, again quite interesting for research purposes and benchmarking.

Despite this, and as already mentioned, a significant part of the publications does not work on commercial games. On the contrary, the trend is to develop proof-of-concept games and environments for experimentation. This trend is mainly due to the difficulty in in modifying, editing, or creating, editing, or creating scenarios useful for experimentation with those games. To bring the game industry closer to research, it would be advisable to provide more tools to allow its manipulation and adaptation for scientific usage. Therefore, it is not surprising that the most used commercial games in this study allow customisation, creation, and modification within the game environment, either by modding tools provided by game companies and unofficial APIs or plugins developed by the user community. This is the case with Unreal Tournament[4] and Starcraft[5].

It is evidenced that a large set of games that appear in studies come from the 2D Arcade scene or are strongly inspired by it [19], [34], [36], [37], [41], [43], [53], [75], [76]. This suggests the opportunity to consider games from this scene in MAS studies due to the clarity on their rules and the ease during the game design and development, among others. Moreover, this suggests the possibility of being able to extrapolate and experiment with games of those coincident genres outside of this scene [38], [47], [91].

B. *Suitability of different genres in MAS problems*

Few papers focused on team formation, performance, and social simulation as MAS problems were found. On the basis of the comments in the previous section, the suitability of the different genres to solve several problems is analysed.

As we have already suggested, Sports and RTS games seem to be suitable for team formation problems, where team members must be grouped before conforming a strategy, defending a position or assigning a task. Concerning performance, proposals are tested on their effectiveness rather than their efficiency. The last feature would be interesting to analyse in certain games where run-time or scalability conditions are present. Certain RTS and FPS games with a large number of units, such as the 'Total War' and 'Warhammer: Vermintide' series, are examples of it.

RPGs and Simulation games seems to be good candidates for testing and experimenting with simulations collective about

[4]UTBots API: https://archive.codeplex.com/?p=utbots

[5]Starcraft I/II APIs: https://github.com/bwapi, https://github.com/Blizzard

MAS on social simulation problems. Moreover, certain simulations attached to social behaviours are interesting in certain genres where communication is a strong component, such as MOBAs and MMORPGs. Among the different strategies to include the simulation of social complex behaviours in these games, the BDI paradigm has been a fast and efficient candidate since they are based on the premise of being close and commensurate with these well-documented behaviours from folk psychology. In addition, its core concepts easily map the perceptions and plans from the beliefs that people use to describe their reasoning and actions in daily life.

Regarding the use of heuristic techniques, it is essential to know the cases in which they are applicable, the strengths, and limits of their use. In general, these are focused on the search for efficient solutions in a reasonable time to the detriment of optimally. Thus, agent plans can be valuable for estimating, inferring, and evaluating behaviours quickly, but may fall short in the search for optimal strategies on games that require minimising specific aspects (i.e., communication, resources, computation, etc.).

C. Research gaps and opportunities

Most of the works are based on the effectiveness and not on the efficiency and scalability of the algorithm. Most of the algorithms presented do not evaluate scalability problems, so their solutions may be weak when increasing the number of agents. Furthermore, to the best of our knowledge, a greater effort should be put into usability studies, especially on these HAI interaction studies where its objective is mainly focused on the user integration with the system. In fact, this is even more important in a game context where interface design is involved in the study.

From the Game AI perspective, we roughly identify two main scopes for agents: control and creative. The first focuses on studying methods to control agents playing games, usually to master the game, have a human-like behaviour, or improve their reasoning or behaviour to be more fun to play against. The second one focuses on improving, building, or generating concrete aspects or content around the game, such as storytelling, maps, landscapes, levels, emerging game mechanics, procedural generation, etc. [3]. Although single agents are more than widespread in both contexts, it was identified a larger corpus in the application of MAS for control rather than creative AI. Games are powerful to stress MAS research because they provide a well-defined scenario and baseline to study all involved aspects in the same fashion as single-agent research, with special emphasis on the unexplored opportunities in creative AI literature, even the possibility to extend it in other aspects such as interaction design and UX.

Furthermore, MAS in virtual games are useful as a first approximation for further robotic scenarios (mainly, proofs-of-concepts, prototypes and preliminary results). Games and robotics share lots of problems, but games are more convenient to work with: they require quite a few physical devices, no specific materials required, are less expensive (including breakdowns), are easily transportable, and can be parallelised or scalable, inter alia.

D. Possible biases or flaws

In this subsection, the different biases and flaws identified during the systematic mapping process are presented, as well as the decisions taken to minimise them and apply the best possible quality of the results.

The word 'Game' has a very broad meaning. Unfortunately, this search for papers based on that word is impractically extensive as matches are included on other topics such as game theory, tabletop games, etc. For this reason, we have made the search more flexible by restricting the scope of the results.

Additionally, papers that do not include related keywords such as '*virtual*', '*graphic*', '*game*', or their variants are out of the first search in this study. However, it is known to us that publications may obviate these adjectives, using only the word 'game' to refer to video games. Finally, some publications do not include the word 'game' since they use the proper name of the game or the games they analyse. To minimise this problem, backward snowballing was performed to find publications of interest that will escape our original query. It should also be mentioned that a significant number of publications that have been discarded, although they made mention of virtual games or graphics, really focus on animation and modelling.

Many papers have been discarded due to the absence of experimentation and evidence. This is due to the fact that these articles performed a proposal but only explained the design and/or its integration, resulting in an on-working paper that presents a framework/environment/game without any implementation. Another important reason for discarding has been studied with questionable experimentation and evidence. An evaluation criterion described in Section II was established to mitigate these cases.

In any case, we are aware of possible works that may have been omitted as a result of the opinion of the authors. Despite our parallel grade-based evaluation inspired by Petersen et al. for efficient decision rules (e.g., reading the introduction and conclusion due to an unclear abstract or reading the full text) [15], this point is critical when applying the inclusion and exclusion criteria based on our reading and reviews. Therefore, in our meta-study, the number of participants in the reading and application of the criteria in the full-text reading stage was extended to 3, as well as the classification and data extraction of the accepted papers. According to this procedure, our strategy was designed to be as inclusive as possible, within a consensus among the authors. Thus, the articles accepted by only one of the reviewer, with the other two rating them as doubtful ($A+B+B=1$). Also those accepted by two authors with the rejection of the third ($A+A+C=1$) were accepted. However, those accepted by only one reviewer and rejected by another ($A+B+C=0$) were rejected as weak.

In any case, in the full-reading stage (see Figure 1), a second review and discussion was included as part of the quality assessment with this grade, and a total of 22 papers were discarded with this grade, which represents 7% of the total number of discarded papers in this phase. The debate on these papers has mainly addressed two issues: The most recurrent was the evaluation conducted by the authors of those papers whose evidence is not clear regarding the application of their agents to the scenario. The other was about discerning which studies rely on games as a scenario and which do not. Many studies are 'inspired' and even contextualise the problem posed through games, but there is no clear implicit use of them. There is also the case of 'games' that do not go beyond a virtual or 3D simulation without a playful component.

Regarding Arcade games, although the possibility of including this category as a genre to cluster related studies was considered, the idea was finally discarded since Arcade could be an ambiguous concept. This is because Arcade games encompass games of very different genres. For example, *OutRun* (Driving), *Virtua Cop* (FPS), and *Dance Dance Revolution* (Music) are more similar to *Gran Turismo*, *Doom*, and *Just Dance* respectively than to each other, despite not being Arcade games these three last ones.

V. Conclusion

Research on Games is a helpful resource to test and challenge AI-based proposals. In the context of Multi-Agent Systems, a great effort has been held over the years, but a big picture of how the field has progressed was missed. Through this SMS, trends, strengths and weaknesses in related studies in this field have been identified. The articles obtained use a wide variety of game genres, but the majority do not use commercial games, since they add complexity and an inflexibility degrees that would compound the final purpose of the research. Games and MAS are designed with various tools to a greater or lesser extent for experimentation, from agent libraries to game engines (such as Unity3D or Unreal Engine, among others).

Machine Learning agents are the most proposed MAS on games, including reinforcement learning and evolutionary techniques. MAS problems faced in the game context are multi-agent planning, task allocation, and human-AI interaction, mainly presented in RTS, Sports and Simulation games. Most of these studies show evidence based on comparisons and test cases with respect to experimentation. However, there is not much experimentation focused on scalability and usability as a counterpart.

In light of the results, some discussions were extracted from this study. First, it is considered that not all genres grant the same opportunities for MAS and depend on the game design. However, a greater effort to study certain MAS problems that fit on concrete genres should be held, especially on multi-agent team formation, scalability and social simulation problems. We consider that games are powerful to stress MAS research because they provide a well-defined scenario and baseline to study all involved aspects in the same fashion as single-agent research.

VI. Future Work

Future work will be focused on delving into the less explored MAS problems in games. Our proposals include studying scalability and team formation problems in RTS games. Alternative lines are to conduct some literature review on the most promising game genres and MAS problems and depth research on MAS on Games from other perspectives such as Usability and User Experience.

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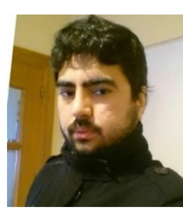

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