Review of the Use of AI Techniques in Serious Games: Decision Making and Machine Learning

Maite Frutos-Pascual and Begoñya García Zapirain

***Abstract*—The video game market has become an established and ever-growing global industry. The health of the video and computer games industry, together with the variety of genres and technologies available, means that video game concepts and programmes are being applied in numerous different disciplines. One of these is the field known as serious games. The main goal of this paper is to collect all the relevant articles published during the last decade and create a trend analysis about the use of certain artificial intelligence algorithms related to decision making and learning in the field of serious games. A categorization framework was designed and outlined to classify the 129 papers that met the inclusion criteria. The authors made use of this categorization framework for drawing some conclusions regarding the actual use of intelligent serious games. The authors consider that over recent years enough knowledge has been gathered to create new intelligent serious games to consider not only the final aim but also the technologies and techniques used to provide players with a nearly real experience. However, researchers may need to improve their testing methodology for developed serious games, so as to ensure they meet their final purposes.**

***Index Terms*—Artificial intelligence, games, intelligent systems, machine learning.**

I. Introduction

Since the beginning of the 21st century, the video game market has become an established and ever-growing global industry. The health of the video and computer games industry, together with the variety of genres and technologies available, means that video game concepts and programs are being applied in numerous different disciplines. One of these is the field known as serious games.

The term serious games was coined by North American researcher Clark Abt in his book *Serious Games* in the 1970s [1]. Although the spirit of this trend has been maintained over the last decades, the technologies, applications, and scope have changed significantly.

Serious games represent a genre designed to be more than "just" fun [2]. Moreover, the educational value associated to serious games goes beyond academic purposes, locating their focus on skill practice and entertainment value during exposure [3]–[6].

The main purpose of a serious game is both to be fun and entertaining, and educational. A serious game is thus designed both to be attractive and appealing to a broad target audience, and to meet specific educational goals [7]. They are designed to foster knowledge, skills, or routine habits in the player.

Serious games span a broad range of fields and areas of expertise. In the literature, serious games were divided into several categories based on different classification schemes. These models can be divided into two main categories: market-based and purpose-based classifications [8].

Several authors established different categories of market-based classification. This segmentation is based primarily on the different "markets" or fields the serious games are developed for. The different segments identified in the literature are as follows:

1) military games, government games, educational games, corporate games, healthcare games, and political, religious, and art games [9];
2) health, public policy, strategic communication, human performance engineering, training and simulation, education, game evaluation [10];
3) educational, social change, military, occupation, and marketing [11];
4) defense, teaching and training, advertising, information and communications, health, culture, and activism [12];
5) K-12 edutainment, higher education, healthcare, corporate, military, nongovernment, and other [13].

Different authors also provide different categories for purpose-based classifications, or intention they were intended to satisfy:

1) advergames, activism games, training and simulation games, edugames, newsgames, and edumarket games [14];
2) business games, health and medicine, news, activism, advergames and political games [15].

Other classification approaches use alternatives to the market/purpose distinction, proposing labels or tags as means of classification [16]. Meanwhile, the G/P/S classification model considers a gameplay, purpose, and scope trio [17]. Finally, classification can also be conducted according to learning principles, target age group, or game platform [12].

The main goal of this paper is to collect all the relevant articles published during recent years and create a trend analysis about the use of certain artificial intelligence algorithms related to decision making and machine learning in the field of serious games. A categorization framework was designed and outlined to classify available articles in the literature. The authors made use of this categorization framework for performing an analysis of the actual use of intelligent serious games.

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The authors are with Deustotech Life [eVIDA], University of Deusto, Bilbao 48015, Spain (e-mail: maitefrutos@deusto.es; mbgarciazapi@deusto.es).

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This paper consists of an analysis of serious games, offering a literary review of their use combined with certain artificial intelligence techniques in the area of decision making and machine learning. Other areas such as path finding were initially considered for study but were not sized enough for further analysis, so they were excluded from this review. The paper is divided into several sections. First, a complete methodology is introduced presenting the form and function of data collected from the literature review. Then, each of the following subsections presents a contextualization and classification of available articles. Finally, the paper ends with the discussion and conclusion section.

II. Method

This paper is the result of a systematic search of the serious game term combined with AI-related parameters. Although the serious game trend as we know it arose during the beginning of the 21st century, due to the amount of studies released in this field, the authors will limit the scope of this review to the last decade, especially between 2005 and 2014.

A. Data Collection

1) Databases Searched: This review was carried out mainly using the search engine provided by the Web of Knowledge. However, searches were also carried out in other electronic databases for this review, for instance, databases particularly related to education, computer science, information technology, social sciences, and health: the Association for Computing Machinery (ACM), IEEE, BioMed Central, Science Direct, EBSCO, Emerald, and PsycINFO.

2) Search Terms: Search terms for games were used in conjunction with terms for possible outcomes, impact of effect games, as well as with related AI parameters. The authors performed a combined search of the terms "game," "serious game," "games," "serious games," "play," "playful," and "game-based learning" in combination with "intelligent," "artificial," "intelligence," "adaptive," "decision trees," "fuzzy logic," "Markov system," "goal orientation," "GOAP," "finite-state machines," "naïve Bayes," "artificial neural network," "case-based reasoning," "support vector machines," "adaptive hypermedia," "dynamic difficulty adjustment," "machine learning," "decision tree," "genetic algorithms," and "reinforcement learning." A third parameter was introduced to narrow down the search, using words for possible outcomes such as "learning," "education," "health," "training," "motivation," "behavior," "skills," "attitude," "military," among others [18].

3) Selection of Papers for Inclusion: Abstracts were selected for the retrieval of the paper if they were judged to include data about the implementation of serious games, including at least one of the displayed AI techniques. In order to achieve this purpose, the papers had to a) include specifically the purpose of the serious game, and its target audience and definition; b) describe the implementation of the AI technique used and its purpose inside the game; and c) they have been published between January 2005 and September 2014. Using these three conditions, 129 out of more than 300 papers met the inclusion criteria and were identified as relevant for the review. Fig. 1 displays inclusion rate per year. Abstracts that clearly implemented a serious game and which seem to have some AI implementation algorithm although its usage was not defined in the abstract were also retrieved for further analysis.

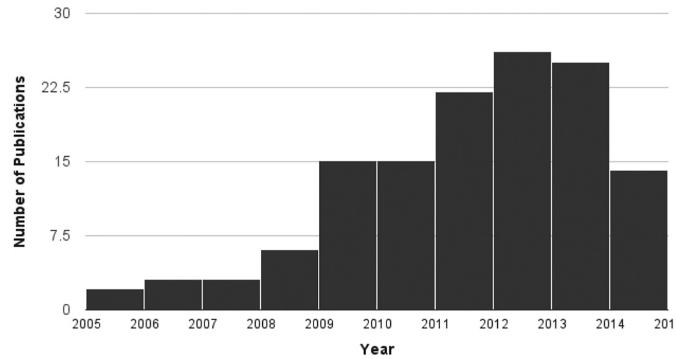

Fig. 1. Articles included in this review per year.

4) Selection of Papers for Exclusion: The papers that did not clearly specify the technique used, the final aim of the serious game, or did not satisfy the conditions outlined in the previous section were not selected for inclusion in this paper.

B. Data Analysis

1) Coding of Papers: The 129 papers meeting the inclusion criteria were coded using a data extraction form that was developed by considering several features related to the outcomes and impacts of the game in several salient dimensions.

2) Information Extraction: Information from the papers was extracted and coded within the following categories.

a) Year and country—Year of publication of the article and the first author's main country of affiliation.

b) AI flagship—This AI flagship classification is based on the work published by G. N. Yannanakis, from the Center of Computer Games Research in Copenhagen. His work presents four key game AI research areas that represent new perspectives [19]. For this review, the following flagships were considered.

   i) Player experience modeling (PEM)—In this category, AI techniques are used for constructing a new model of player experience. This can stem from different types of data collected from the players. These PEM approaches are: objective (collecting data by monitoring changes in players' physiology; these bodily alterations may assist in adapting games to the users state and behaviors); subjective (subjective player experience modeling based on self-reporting; this can guide machine learning algorithms to capture different aspects of player experience); and gameplay (any element derived from the interaction between the player and the game).

   ii) Procedural content generation—This flagship refers to the development of algorithms that generate game content automatically. These elements may affect player experience.

iii) Game data mining—Games where users' data are collected during gameplay with the aim of addressing specific questions.

c) AI usage—This category classifies the final purpose of the AI implementation for each of the included articles [for example, for classifying users, altering nonplayer character (NPC) behaviors, adapting gameflow, among others].

d) Market/purpose classification as follows:
   i) serious games market—classify the articles based on the different "markets" or fields the serious games were developed for;
   ii) serious games purpose—classify the references based on the intention the serious games were developed for.

e) Platform/delivery—Platforms for delivery of the game were classified as PC, mobile/tablet, online game, or others.

f) Type—This category refers to the project type. This is divided into: new developments of serious games, new frameworks for building serious games, and other (research studies or game engines, among others).

g) Testing procedure—For studies tested with real users, further information regarding the sample size, gender balance, and age range was analyzed and coded. For articles with different testing procedures, their study design and data analysis were reviewed and coded.

h) Publication channel—Publishing medium was also analyzed and coded. The articles were divided into: type I—international journals with impact factor; type II—international journals; type III—international conferences, workshops, and symposia; and type IV—book chapters.

C. The Paper's Outline

The authors will discuss all these categories in two main fields of AI: decision making (Section III) and machine learning (Section IV). Each section reviews several methods and algorithms related to those areas. The authors have selected those most implemented in the field of serious games for their inclusion in this paper. Each section outlines the different trends in the design and development of AI in serious games. These trends are based on the different coded categories included in the methodology section. Finally, global tendencies are analyzed in Section V.

III. Decision Making

This section deals with one of the most popular techniques inside the storyline of serious games: the decision making field.

These algorithms and techniques are used for logical and rational decision-making processes based on the information compiled by the system. The input of the decision-making systems is the previously collected knowledge, and the output is an action request [20].

These algorithms and techniques are very popular in the design and development of serious games, i.e., Sordoni et al. used decision-making agents in a game that was oriented toward raising people's awareness about the importance of making rational decisions concerning natural resources management in protected environments [21]. Cantwell et al. developed a collaborative exergame for the elderly, in which game speed and difficulty were adjusted in the light of user profile and performance [22]. The following subsections provide information about other developments classified by specific AI techniques within the field of decision making.

A. Decision Trees

The main objective of decision trees is to create a prediction model on the basis of a set of decision rules obtained from compiled data during system performance. These decision trees have been used throughout the literature by several authors. This section categorizes the latest and most relevant publications using this technique applied to the serious games field.

Twenty seven articles described research that employed decision trees and could be further analyzed and coded following the categories outlined in Section II. Refer to Table I for a complete list of coded articles in this section.

1) AI Flagship: The vast majority of the coded articles (19 out of 27) fall into the category of "PEM—gameplay based." For example, Costa et al. were focused on the enhancement of executive memory and attention. The internal mechanisms of this serious game were based on a decision tree that considered players' errors and progresses to create a customized gameplay experience [23].

Four studies made use of game data mining. Keshtkar et al. presented a framework based on data mining techniques and language processing approaches for evaluating players' personality and behavior while using the educational game *Land Science* [24]. The remaining four did not correspond to any AI flagship.

2) AI Usage: Decision trees were implemented for modeling the game flow in 14 out of 27 articles, therefore, providing customized experiences to users based on their interaction with the game. This was implemented as a set of decision trees for the internal mechanism of the game [25]–[29].

In eight of the revised articles, the decision trees were used for assessing motivation and users' states while playing, letting the system to obtain and analyze users' behavior information [30]–[32].

Two articles designed systems based on decision trees to involve players in further analysis or even to let users build them. For example, Haworth et al. displayed decision trees during gameplay to assess the users' effectiveness in analytic reasoning while playing in a logic labyrinth-style game [33]. Good et al. designed the scientific discovery game *The Cure*. This game was centered on the task of gene selection for breast cancer survival. The objective of each level is to choose a set of genes that produces a better decision tree classifier, which is stored for the next time improving the system [34].

3) Categorization of Games: The articles were classified according to the following features.

TABLE I
DECISION TREES AND SERIOUS GAMES: CODED ARTICLES

Authors	Country	Year	AI Flagship	AI Usage	Type	Platform	SG Market	SG Purpose	Participants				Publication*	Reference
									Total	Males	Females	Age		
Good *et al.*	US	2014	Massive Scale Game Data Mining	Transparent	Development	Online	Health	Health	1077	–	–	–	Type II	(34)
Castro-Sanchez *et al.*	GB	2014	–	Gameflow	Development	Mobile	Health	Training	–	–	–	–	Type II	(41)
Frutos-Pascual *et al.*	ES	2014	PEM - Gameplay	Assistance	Development	Online	Health	Health	17	10	7	12 - 19	Type I	(30)
Keshtkar *et al.*	US	2014	Massive Scale Game Data Mining	Assessing	Framework	PC	Business	Training	12	–	–	6 - 12	Type IV	(24)
Sabourin *et al.*	US	2013	PEM - Gameplay	Gameflow	Development	PC	Educational	Edugames	260	129	131	13.4 (SD = 0.57)	Type II	(25)
Lin *et al.*	TW	2013	PEM - Gameplay	Suggestion	Development	PC	Educational	Training	92	48	44	18 - 26	Type I	(42)
Moya *et al.*	ES	2013	–	Optimization	Framework	PC	–	–	35	–	–	6 - 70	Type I	(44)
Horan and Gardner	UK	2013	PEM - Gameplay	Gameflow	Development	Online	Political	Edugames	6	–	–	–	Type IV	(26)
Petridis *et al.*	UK	2013	PEM - Gameplay	Gameflow	Development	PC	Culture and activism	Edugames	5	–	–	–	Type II	(27)
Hussaan and Sehaba	FR	2012	PEM - Gameplay	Assessing	Development	PC	Health	Edugames	–	–	–	–	Type IV	(45)
Fu-Hsing *et al.*	TW	2012	Massive Scale Game Data Mining	Assessing	Framework	Online	Educational	Activism	8	4	4	11 - 12	Type II	(40)
Parsons *et al.*	NZ	2012	PEM - Gameplay	Gameflow	Development	Mobile	Business	Training	14	–	–	–	Type III	(35)
Goulding *et al.*	UK	2012	PEM - Gameplay	Evaluation	Development	PC	Educational	Training	–	–	–	–	Type I	(46)
Rijcken *et al.*	NL	2012	PEM - Gameplay	Gameflow	Development	Online	Culture and activism	Activism	–	–	–	–	Type II	(38)
Hussaan *et al.*	FR	2011	PEM - Gameplay	Gameflow	Development	PC	Health	Edugames	–	–	–	–	Type III	(28)
Chiang	TW	2011	Massive Scale Game Data Mining	Assessing	Development	PC	Business	Training	Tested with different games				Type III	(36)
Qin *et al.*	CN	2011	PEM - Gameplay	Assessing	Development	PC	Health	Training	–	–	–	–	Type I	(32)
Van der Spek	NL	2011	PEM - Gameplay	Gameflow	Development	PC	Health	Training	41	36	5	23.3 (SD = 1.89)	Type I	(43)
Santos *et al.*	BR	2011	PEM - Gameplay	Assessing	Development	PC	Health	Health	80	–	–	10 - 17	Type III	(31)
Ghergulescu and Huntean	IE	2011	PEM - Gameplay	Assessing	Framework	PC	Educational	Edugames	–	–	–	–	Type III	(47)
Costa *et al.*	BR	2010	PEM - Gameplay	Gameflow	Development	PC	Health	Health	–	–	–	–	Type III	(23)
Haworth *et al.*	CA	2010	–	Transparent	Development	PC	Educational	Training	–	–	–	–	Type II	(33)
Vidani and Chittaro	IT	2009	PEM - Gameplay	Gameflow	Development	PC	Health	Training	–	–	–	–	Type III	(48)
Bellotti *et al.*	IT	2009	PEM - Gameplay	Gameflow	Framework	PC	Educational	Training	–	–	–	–	Type I	(49)
Lilly and Warnes	UK	2009	–	Gameflow	Framework	Mobile	Business	Edugames	–	–	–	–	Type IV	(37)
Kim *et al.*	US	2009	PEM - Gameplay	Gameflow	Development	PC	Military	Training	31	–	–	–	Type II	(39)
Tang and Hannegham	MY	2008	PEM - Gameplay	Gameflow	Framework	PC	Educational	Training	–	–	–	–	Type III	(29)

*(a) Type I: International journals with impact factor. (b) Type II: International journals. (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books.

1) Serious games market: The most common market for serious games employing decision trees was health with ten papers out of 27. Next was the educational with eight papers, then business with four papers [24], [35], [36], [37], and culture and activism with two papers [38], [27]. Remaining three articles were classified as political [26], military [39], and uncategorized, respectively.
2) Serious games purpose: Regarding their purpose, selected articles were classified as follows: four papers under the category of health [23], [31], [30], [34], [13] under training field; seven papers under edugames; two papers under activism-related games [40], [38]; and final paper was uncategorized.
3) Platform/delivery: Nineteen out of the 27 analyzed serious games were designed for PC, while five were for an online use [30], [34], [26], [40], [38] and three were specifically developed for mobile devices [41], [35], [37].
4) Project type: The majority of analyzed papers were new developments of serious games, while the remaining seven papers were framework proposals and design guidelines combining decision trees and serious games.

4) Sample of Participants: Out of the 27 articles included for revision in this section only 14 included any information about testing procedures. Eight out of those 14 outline further information about sample's age range. Only five included detailed description of the users in terms of gender and age [30], [25], [42], [43], [40].

5) Publication Type: Publication channels were well balanced, with seven articles published in international journals with impact factor and eight papers published in international journals without impact factor. Another eight were presented in international conferences, workshops, and symposia, and last four were published as chapters in books.

B. Fuzzy Logic

Fuzzy logic is based on approximate reasoning. It goes beyond binary approximations, and was designed to cope with gray areas that go beyond true or false [20].

Fuzzy logic is relatively popular in the video game industry. It is considered to be of great utility when employing probabilistic methods to reflect any kind of uncertainty [50]. The most relevant publications are briefly introduced below and classified in the terms outlined in Section II. Sixteen articles employed fuzzy logic. Refer to Table II for a complete list of the coded articles in this section.

1) AI Flagship: Eleven out of 16 articles fall into the category of "PEM—gameplay based." One example is the serious game *Karo* which infers gameplay outcomes based on players' decisions and actions [51].

Three articles were classified under the "PEM—objective" flagship as they made use of different movement and biological sensors together with user data for customizing the gameplay [52], [53].

One article was categorized as "procedural content generation." This serious game was focused on the training of commanders in their strategies after toxic chemical spillages. It combined fuzzy logic with artificial neural networks for modeling NPCs behaviors.

The last article was classified under the "game data mining" label. This game was developed as a multiagent-based model of team play, for characterizing individual personalities by Myers–Briggs-type indicator (MBTI) [54].

2) AI Usage: Fuzzy logic was implemented for addressing a wide range of possibilities throughout the literature.

The most common usage of fuzzy logic in serious games was as techniques for adapting the gameplay, with six references in this section.

TABLE II
FUZZY LOGIC AND SERIOUS GAMES: CODED ARTICLES

Authors	Country	Year	AI Flagship	AI Usage	Type	Platform	SG Market	SG Purpose	Participants				Publication*	Reference
									Total	Males	Females	Age		
Karime et al.	AE	2014	PEM - Objective	Adapt the gameplay	Framework	PC	Health	Health	–	–	–	–	Type I	(52)
Pirovano et al.	IT	2014	PEM - Gameplay	Teach Fuzzy logic	Development	PC	Educational	Edugame	–	–	–	–	Type I	(60)
Petit dit Dariel et al.	FR	2013	PEM - Gameplay	Adapt the gameplay	Development	PC	Health	Training	–	–	–	–	Type I	(66)
Zaldivar et al.	MX	2013	PEM - Gameplay	Teaching fuzzy logic	Platform	PC	Educational	Edugame	–	–	–	–	Type II	(61)
Oliveira et al.	BR	2013	PEM - Gameplay	Adapt the gameplay	Development	PC	Business	Training	–	–	–	–	Type III	(63)
Farhangian et al.	NZ	2013	Game Data Mining	Classify users	Research	PC	Social Change	Training	Simulation study using NetLogo				Type III	(54)
De Oliveira et al.	BR	2012	PEM - Objective	Assess user state	Development	PC	Health	Health	–	–	–	–	Type III	(55)
Pirovano et al.	IT	2012	PEM - Objective	Monitor exercises execution online	Development	Online - PC	Health	Health	–	–	–	–	Type III	(53)
Saraiva et al.	BR	2011	PEM - Gameplay	Adapt the gameplay	Development	Online	Training	Training	–	–	–	–	Type III	(64)
Brasil et al.	BR	2011	PEM - Gameplay	Actions Gameplay	Development	Online	Training	Edugame	–	–	–	–	Type III	(65)
Imbeault et al.	CA	2011	PEM - Gameplay	Assess user state	Development	PC	Health	Training	20	–	–	–	Type III	(56)
Buditjahjanto and Miyauchi	ID	2011	PEM - Gameplay	Infer NPC behaviour	Development	PC	Social Change	Edugame	–	–	–	–	Type I	(58)
Shen et al.	SG	2010	PEM - Gameplay	Adapt the gameplay	Development	PC	Educational	Edugame	–	–	–	–	Type IV	(62)
Cai et al.	SG	2009	PEM - Gameplay	Foster immersion	Development	PC	Health	Edugame	–	–	–	–	Type I	(57)
Balas et al.	CZ	2008	PEM - Gameplay	Adapt the gameplay	Development	PC	Social change (civics)	Edugame	–	–	–	–	Type III	(51)
Djordjevich et al.	US	2008	Procedural Content Generation	Infer NPC behaviour	Development	PC	Military	Training	–	–	–	–	Type III	(59)

*(a) Type I: International journals with impact factor; (b) Type II: International journals; (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books.

TABLE III
MARKOV SYSTEMS AND SERIOUS GAMES: CODED ARTICLES

Authors	Country	Year	AI Flagship	AI Usage	Type	Platform	SG Market	SG Purpose	Participants				Publication*	Reference
									Total	Males	Females	Age		
Su et al.	GB	2014	Procedural Content Generation	Adapt gameplay	Framework	PC	Educational	Edugames	Simulated learners + 278 real				Type II	(70)
Navarro-Newball et al.	CO	2014	PEM - Gameplay	Infer information from players	Development	PC	Health	Health	–	–	–	–	Type I	(73)
Sucar *et al.*	MX	2013	PEM - Gameplay	Adapt gameplay	Development	PC	Health	Health	6	Feasibility pilot study with chronic stroke patients			Type I	(75)
Su *et al.*	TW	2013	Procedural Content Generation	Adapt gameplay	Framework	PC	Educational	Edugames	Simulated learners + 278 real				Type III	(70)
Derbali *et al.*	CA	2013	PEM - Objective	Assess players' motivation	Development	PC	Educational	Edugames	41	20	21	23.7 (group 1) 25.3 (group 2)	Type III	(69)
Rafferty *et al.*	US	2012	Game Data Mining	Infer information from players	Framework	Online	Educational	Edugames	225	–	–	–	Type III	(72)
Bouchard *et al.*	CA	2012	PEM - Gameplay	Adapt gameplay	Guidelines	PC	Health	Health	–	–	–	–	Type IV	(74)
Neto *et al.*	PT	2011	PEM - Gameplay	Adapt gameplay	Development	PC	Culture and activism	Edugames	More than 1400 (data not analyzed)				Type III	(77)
Muñoz *et al.*	IE	2010	PEM - Gameplay	Adapt gameplay	Development	PC	Educational	Edugames	28	–	–	University Students	Type IV	(68)
Johnson *et al.*	US	2007	PEM - Gameplay	Adapt gameplay	Development	PC	Military	Edugames	8	–	–	–	Type III Type IV	(78; 79; 76)

*(a) Type I: International journals with impact factor; (b) Type II: International journals; (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books.

Fuzzy systems were also implemented for assessing user state during gameplay, classifying users' state [54], [55] or managing feedback during the game [56].

Fuzzy systems were also considered for monitoring and promoting immersive experiences [53], [57], as well as for the controlling of NPCs [58], [59].

Fuzzy logic was also implemented in serious games for actually teaching fuzzy logic, as means of observing the behaviors of virtual characters [60] or robots [61] guided by a certain set of rules during gameplay.

3) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: Six out of 16 articles in this section belonged to the health category inside the serious games market. The market with the second highest number of articles in this section are education [60]–[62], social change [54], [58], [51], and business [63], [64], [65] fields with three references each. The military market [59] did also have representation inside the fuzzy logic implementation.

b) Serious games purpose: The respective purposes of the identified publications in this section were quite balanced: Three articles belonged to the health category, six articles were related to training, and the remaining seven articles were classified as edugames.

c) Platform/delivery: Out of the 16 included articles, 13 were designed for PC while the remaining three were available online.

d) Project type: Thirteen of the reviewed studies were concerned with new serious games software development, while the remaining three were categorized as platform [61], framework [52], and research study [54].

4) Sample of Participants: All the outlined articles were focused on internal mechanisms, designs, or algorithms involved in the development of serious game, and did not display data about user interaction, performance, or game efficiency and efficacy. However, one of the articles describes a testing procedure using NetLogo for the simulation study [54].

5) Publication Type: Publication channels were not balanced in this section, with five articles published in international journals with impact factor, one article published in an international journal, seven articles published in international conferences, workshops, and symposia, and three articles published as chapters in books.

C. Markov Systems

Markov systems go a step further than fuzzy logic, assigning a meaning to the values of truth or belonging. Markov systems are memoryless, and they are represented as a set of finite transitions among a determined number of possible states [67].

Reviewing the literature inside the serious games field, there are some references to their usage. The authors found ten articles that met all the inclusion criteria outlined in Section II-A3. Refer to Table III for a complete list of coded articles in this section.

1) AI Flagship: Six out of ten articles fell into the category of "PEM—gameplay based." This is the case of the game *PlayPhysics* which was developed for teaching physics to engineering students and made use of hidden Markov models for adapting the gameplay based on players' interaction [68].

One article was classified under the "PEM—objective" flagship. The serious game *Heap Motiv* implemented the Keller

TABLE IV
GOAL-ORIENTED BEHAVIORS AND SERIOUS GAMES: CODED ARTICLES

Authors	Country	Year	AI Flagship	AI Usage	Type	Platform	SG Market	SG Purpose	Participants				Publication*	Reference
									Total	Males	Females	Age		
Qu *et al.*	NL	2013	Procedural Content Generation	Evaluate users' responses	Framework	PC	–	–	40	Real world + Virtual reality			Type I	(87)
Yu *et al.*	UK	2012	Game Data Mining	Generate assembly plans	Development	PC	Business	Training	–	–	–	–	Type III	(84)
Alvarez-Napagao *et al.*	ES	2012	Procedural Content Generation	Model scenarios and NPC behaviors	Framework	PC	–	–	–	–	–	–	Type III	(82)
Alvarez-Napagao *et al.*	ES	2010	Procedural Content Generation	Model scenarios and NPC behaviors	Framework	PC	–	–	–	–	–	–	Type III	(82)
Jepp *et al.*	PT	2010	PEM-Gameplay	NPC behaviors	Framework	PC	–	–	–	–	–	–	Type III	(86)
Rebolled-Mendez *et al.*	UK	2009	PEM - Gameplay	NPC Behaviour	Framework	PC	Educational	Edugames	–	–	–	–	Type III	(85)

*(a) Type I: International journals with impact factor; (b) Type II: International journals; (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books.

ARCS motivational model along with biological variables such as the heart rate and EEG to identify users' state and establish different motivational strategies [69].

Two studies were categorized as "procedural content generation." They were about a framework designed for computer-assisted language learning games using trained Markov decision processes [70], [71].

Last, one article was categorized as "game data mining," which presented a new game-based approach for conducting cognitive science experiments. They implemented Markov decision processes to infer cognitively relevant information from players' actions during gameplay [72].

2) AI Usage: As described in earlier sections, more than half of all articles considered, seven out of ten, were focused on adapting the gameplay.

Markov systems were also implemented for collecting information from players [72], [73] and assessing player motivation [69].

3) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: The educational market was the most referenced, with five articles in this category. Health had three articles [74]–[75]. Military [76] and culture and activism [77] fields were balanced with one article each.
b) Serious games purpose: Regarding the final purpose of the reviewed studies, the vast majority of them were categorized as edugames. The three remaining articles were considered to have a health-related purpose.
c) Platform/delivery: All but one of the analyzed studies were designed and implemented for PC. The remaining article was developed as an online tool [72].
d) Project type: Seven out of ten of the reviewed studies were new serious games software developments, while three of the remaining articles were categorized as frameworks [70]–[72]. Last, one article presented a set of guidelines for designing serious games [74].

4) Sample of Participants: Eight out of ten articles were tested in one way or another with real participants. The *Heap Motiv* game gave detailed description about the sample characteristics and the experiment setting [69]. Su et al. tested their framework proposal with both simulated learners and over 250 real participants [70], [71], but they did not specify gender segmentation, nor age range. The game *PlayPhysics* was tested with 28 university students [68], while the *Solis Curse* game was tested by over 1400 real users, though the authors did not provide any further analysis of these data [77].

5) Publication Type: Publication channels in this section were: two articles published in international journals with impact factor, one study was available in an international journal, and five articles were published in international conferences, workshops, and symposia. The remaining two studies were published as book chapters.

D. Goal-Oriented Behavior

Reviewing the literature, goal-oriented behavior has been used for providing NPCs with a set of behaviors and guidelines for making them more realistic. Goal-oriented behavior deals with a series of techniques that produce action sequences so as to achieve a determined goal [80]. Goal-oriented action planning (GOAP) is composed of a set of goals and actions. One of its main goals is determined by the properties of the environment. Actions are described in terms of their effects on the environment and they are formulated with a planner [81].

Only six articles fulfilled the inclusion criteria of the goal-oriented behavior category. Refer to Table IV for the complete list of coded articles in this section.

1) AI Flagship: Two out of the six included articles fall into the category of "PEM—gameplay based."

Three studies were categorized as "procedural content generation." Two of them introduced the framework *cOnciens*. This framework described a set of tools for game AI developers. It was focused on model gaming scenarios using social structures [82], [83].

The last reviewed study in this section was categorized as "game data mining," which implemented techniques within the video game industry in a mechanical assembly line [84].

2) AI Usage: The majority of articles included in this section, four out of six, implemented GOAP techniques for controlling NPC behavior [85], [86]. Two of these four were additionally focused on modeling scenarios during gameplay [82], [83].

One article implemented the GOAP techniques for evaluating users' responses [87].

A final article was focused on gameplay assembly plans. The authors tested feasibility through the use of a game focused on car repair, applying GOAP to the decision process of repairing [84].

3) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: One article was categorized as educational [85], and another was labeled under the field of business [84]. The remaining four studies were

TABLE V
RULE-BASED SYSTEMS AND SERIOUS GAMES: CODED ARTICLES

Authors	Country	Year	AI Flagship	AI Usage	Type	Platform	SG Market	SG Purpose	Participants				Publication*	Reference
									Total	Males	Females	Age		
Sehaba and Hussaan	FR	2013	PEM - Gameplay	Evaluate users' performance	Framework	PC	Educational	Edugame	Comparative study between framework and expert system				Type II	(98)
Haladjan et al.	DE	2012	Procedural Content Generation	Users can create their own games	Framework	Mobile devices	Educational	Edugame	Multiple-case and quasi-experimental study				Type III	(90)
Khayat et al.	EG	2012	PEM - Gameplay	Assess users	Development	Online	Health	Training	–	–	–	–	Type III	(89)
Ward et al.	US	2012	PEM - Gameplay	Guide users	Development	PC	Educational	Edugame	11	7	4	11.1	Type III	(93)
Rojas-Barahona	FR	2012	PEM - Gameplay	Respond to players utterances	Development	PC	Business	Training	40	–	–	–	Type III	(94)
Souza *et al.*	BR	2009	PEM - Gameplay	Model NPC's behavior	Development	PC	Business	Training	–	–	–	–	Type III	(95)
Arya et al.	CA	2009	–	Identify user emotions	Framework	PC	Health	Edugame	50	–	–	University Students	Type II	(91)
Patton *et al.*	US	2008	PEM - Gameplay	Evaluate users' performance	Development	Tablet PC	Educational	Edugame	16	–	–	Senior and Graduate level students	Type III	(92)
Core, Gomboc et al.	US	2006	PEM - Gameplay	Rule based behaviors	Development	PC	Business	Edugame	–	–	–	–	Type III	(?)
El Rhalibi *et al.*	UK	2005	PEM - Gameplay	Gameflow	Development	PC	Culture and activism	Edugame	–	–	–	–	Type III	(97)

*(a) Type I: International journals with impact factor; (b) Type II: International journals; (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books

uncategorized as regards the serious games market. These four articles proposed a customizable framework able to be used in a variety of serious games' markets [82], [83].

b) Serious games purpose: Considering the purpose of the game, the included articles were divided as follows: One article was considered to be under the field of training [84], while another was classified under the edugames field [85]. The remaining four were uncategorized as regards their purpose.

c) Platform/delivery: All the revised studies were designed and/or implemented for PC.

d) Project type: Five out of the six revised articles were framework proposals for serious games development. The remaining study was a new development for applying video game techniques in a mechanical assembly line [84].

4) Sample of Participants: Only one article was tested with real participants [87]. The serious games framework proposed by Alvarez-Napagao et al. was tested in various settings and serious games for assessing its usability [82], [83].

5) Publication Type: One of the articles was published in an international journal with impact factor [87], while the remaining five were published in international conferences, workshops, and symposia.

E. Rule-Based Systems

Rule-based systems are outlined as a way of storing and handling knowledge to interpret information in an efficient way [88]. The most common use of this in the field of serious games is by using a set of preimplemented guidelines using boolean operators in an expert system for assisting in decision making and tactical movements during the game.

Regarding the field of serious games, ten articles were found implementing these techniques (see Table V for a complete relation of coded articles).

1) AI Flagship: The majority of reviewed articles in this category, eight out of ten, fall into the category of "PEM—gameplay based." For example, Khayat et al. create customized sets of mini-games for children based on their performance in an IQ test and their responses to previous exercises [89].

One article was categorized as "procedural content generation." This study introduced a framework for creating adaptive educational serious games, giving the players the opportunity to create their own play experience [90].

The remaining study was uncategorized as regards its AI flagship.

2) AI Usage: Four out of ten studies were related to the assessment and evaluation of users in one way or another. For example, Arya et al. developed a fuzzy-rule-based system that studies facial expressions and social competencies in children with ASD to evaluate their emotions [91] while Patton et al. developed a serious game for guiding students with calligraphy problems. They evaluated user performance using a rule-based system [92].

Two articles made use of AI techniques with the end purpose of guiding users and responding to their utterances [93], [94].

Two studies were focused on modeling NPCs behaviors as a rule-based system based on the requirements related to the character-based game development [95] or the iteration between some predefined behaviors of the game [96].

The remaining two articles that used AI techniques were related to the player experience. Players were able to create their own games using a set of rule-based decisions inside a framework for creating adaptive educational games [90]. The last study was focused on inferring players' gameflow based on the recorded data and a set of rules [97].

3) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: Two articles were categorized as part of the health market [89], [91], and another four were labeled under education [92], [98], [90], [93]. Three studies were classified under business [94]–[96]. The remaining study was labeled under culture and activism [97].

b) Serious games purpose: Considering the purpose of the game, the articles were divided as follows: Seven articles were considered to be edugames, while the remaining three were labeled under the term of training.

c) Platform/delivery: While the majority of the studied serious games in this section were developed for PC (seven out of ten), the remaining three were implemented for tablet PC [92], mobile devices [90], and for online uses [89].

d) Project type: Seven out of the ten consulted articles were new developments of serious games. The three remaining studies were framework proposals for building serious games.

4) Sample of Participants: Four of the articles were tested with real participants, one of which gives accurate data regarding the gender and age of the participants [93]. Two of the

TABLE VI
FINITE-STATE MACHINES AND SERIOUS GAMES: CODED ARTICLES

Authors	Country	Year	AI Flagship	AI Usage	Type	Platform	SG Market	SG Purpose	Participants				Publication*	Reference
									Total	Males	Females	Age		
Tan et al.	AU	2013	PEM - Objective	Control characters	Development	PC	Health	Training	2	1	1	7-10	Type III	(101)
Li et al.	US	2013	Game Data Mining	Evaluate users	Development	PC	Health	Training	67	–	–	28.4 (SD=11.2)	Type III	(104)
Morgan et al.	US	2013	PEM - Gameplay	Evaluate users	Development	PC	Business	Edugame	Tested but not further information				Type III	(111)
Wattanasoontorn et al.	ES	2012	PEM - Gameplay	Gameflow	Development	PC	Health	Training	–	–	–	–	Type III	(106)
Nyoman *et al.*	ID	2012	PEM - Gameplay	Gameflow	Development	PC	Educational	Training	–	–	–	–	Type III	(105)
Rehm and Leichtenstern	DK	2012	PEM - Objective	Evaluate users	Development	Mobile	Culture and Activism	Training	20	15	5	–	Type I	(102)
Sisler et al.	CZ	2012	PEM - Gameplay	Gameflow	Development	PC	Educational	Edugame	Feasability study. Game not tested				Type III	(118)
Ines and Abdelkader	FR	2011	PEM - Objective	Control characters	Development	PC	Health	Health (Rehab)	3	–	–	20-30	Type III	(103)
Szczesna et al.	PL	2011	PEM - Gameplay	Gameflow	Development	PC	Educational	Training	–	–	–	–	Type III	(100)
Wendel et al.	DE	2010	PEM - Gameplay	NPC Behaviours	Development	Online	Business	Edugame	–	–	–	–	Type IV	(114)
Sagae et al.	US	2010	PEM - Gameplay	Game behaviour	Development	PC	Educational	Training	–	–	–	–	Type III	(109)
Irvine and Gongora	GB	2010	–	NPC Behaviours	Methodology	PC	–	–	–	–	–	–	Type III	(112)
Yessad et al.	FR	2010	PEM - Gameplay	Customize gameplay	Authoring Environment	PC	Educational	Edugame	The approach was tested with the Serious Game Blossom Flowers.				Type III	(107)
Rankin and Vargas	AU	2009	–	Build the game behaviour	Development	PC	Educational	Edugame	–	–	–	–	Type III	(108)
Silverman et al.	US	2009	PEM - Gameplay	–	Development	PC	Culture and Activism	Edugame	–	–	–	–	Type IV	(116)
Florez-Puga et al.	ES	2008	PEM - Gameplay	NPC Behaviours	Development	PC	Educational	Edugame	–	–	–	–	Type III	(113)
Binsubaih et al.	UK	2006	PEM - Gameplay	Gameflow	Development	PC	Educational	Training	56	–	–	–	Type II	(117)
Darken et al.	US	2007	–	Code Games	Game Engine	PC	Military	Training	–	–	–	–	Type III	(115)
Duggan et al.	IE	2005	–	Build the game world	Development	PC	Educational	Edugame	–	–	–	–	Type III	(110)

*(a) Type I: International journals with impact factor; (b) Type II: International journals; (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books.

remaining three clarify that the preliminary tests were performed with undergraduate students. The last does not give any further information about the sample, only on the number of participants.

Two out of the three included frameworks in this section provide data about their performance. Both of them were tested for assessing their strengths [90], [98].

Four articles did not provide any information about participants or experimental procedures.

5) Publication Type: Eight of the reviewed articles were published in international conferences, workshops, and symposia. The remaining two articles were published in international journals.

F. Finite-State Machines

Finite-state machines constitute a mathematical computational model. They are represented as an abstract system that can be on one of a finite number of states each time. Specific events or conditions are needed to switch between different states, these switches being named as transitions. One specific finite-state machine is defined by a list of states and a set of conditions for switching between them [99].

Reviewing the literature concerning this technique, 19 articles were found. They were categorized as regards the characteristics outlined in Section II. Table VI illustrates all the coded studies.

1) AI Flagship: The majority of reviewed articles in this category, 11 out of 19, fall into the category of "PEM—gameplay based." For example, the serious game *Mission—Master Your Fear* is a therapeutic game for kindergarten children. The different levels and game scenarios were based on children's previous interaction and they were implemented as a finite-state machine [100].

Three studies were categorized as "PEM—objective." One of these articles included voice recognition algorithms for processing players' speech [101] while the other two implemented motion recognition systems based on accelerometers [102], [103]. Using these sensors they were able to evaluate hand position, gesture recognition, and velocity among others for difficulty adjustment.

One article was labeled under the "game data mining" category. In the serious game *Missing*, the developers applied machine learning techniques to the game log so as to evaluate different strategies and demographic variances between players [104].

The remaining four studies were uncategorized as regards their AI flagship.

2) AI Usage: The purpose of implementing finite-state machines varies between a wide range of categories. The most common was for controlling the gameflow. Six articles were found in this field. They used finite-state machines for switching between levels [100], [105], controlling the CPR actuation [106], or customizing the gameplay [107], among others.

Three articles were found in each of the following categories: building the game behavior [108]–[110], evaluating users [104], [111], [102], and controlling NPCs behaviors [112]–[114].

Two articles used finite-state machines for controlling virtual characters in the game [103], [101].

The remaining article was developed as a game engine where AI techniques were available in a high-level scripting language [115]. The remaining article was uncategorized as regards the AI purpose.

3) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: Four articles were categorized as for the health market [101], [104], [106], [103], and nine studies were under educational. Two articles were under business [111], [114]. Another two were under culture and activism [102], [116]. One article was categorized in the military field [115]. The remaining article was uncategorized.

b) Serious games purpose: Considering the purpose of the game, the articles were divided as follows: Eight articles were considered to be on edugames, while nine were labeled under training, and only one was categorized as health related. The remaining article was uncategorized.

TABLE VII
AI FLAGSHIP: DECISION-MAKING TRENDS

Technique	N	Player Experience Modeling			Procedural	Game	Uncat.
		Subjective	Objective	Gameplay	Content Generation	Data Mining	
Decision Trees	27	0	0	19	0	4	4
Fuzzy Logic	16	0	3	11	1	1	0
Markov Systems	10	0	1	6	2	1	0
Goal Oriented Behavior	6	0	0	2	3	1	0
Rule-based Systems	10	0	0	8	1	0	1
Finite-State Machines	19	0	3	11	0	1	4
Total:	88	0	7	57	7	8	9
Percentage:	100	0.00%	7.95%	64.77%	7.95%	9.09%	10.23%

TABLE VIII
SERIOUS GAMES PURPOSE: DECISION-MAKING TRENDS

Technique	N	Health	Education	Business	Culture and Activism	Social Change	Political	Military	Uncat.
Decision Trees	27	10	8	4	2	0	1	1	1
Fuzzy Logic	16	6	3	3	0	3	0	1	0
Markov Systems	10	3	5	0	1	0	0	1	0
Goal Oriented Behavior	6	0	1	1	0	0	0	0	4
Rule-based Systems	10	2	4	3	1	0	0	0	0
Finite-State Machines	19	4	9	2	2	0	0	1	1
Total:	88	25	30	13	6	3	1	4	6
Percentage:	100	28.41%	34.09%	14.77%	6.82%	3.41%	1.14%	4.55%	6.82%

c) Platform/delivery: The majority of included serious games in this section were developed for PC. The remaining two were implemented for mobile devices [102] and for being used online [114].
d) Project type: Sixteen out of the 19 consulted articles were new developments of serious games. The three remaining studies were classified as design methodology [112], game engine [115], and authoring environment [107].

4) Sample of Participants: Eight articles were tested with real participants, three of which gave accurate data regarding the gender and age of the participants [101], [102], [117]. Two of the remaining three clarified the age range of participants. The authors were not able to access detailed information on participants in the remaining article.

The feasibility of the serious game *Stories from the History of Czechoslovakia* was tested but no further analysis of system usability was outlined in the study [118].

The authoring environment *SeGAE* was applied to the serious game *Blossom Flowers* for adapting different aspects of the game and the character, proving its efficiency [107].

The remaining 11 articles did not give any further information whether they have been tested with real participants.

5) Publication Type: Fifteen articles were published in international conferences, workshops, and symposia. The remaining four articles were made available through international journals with impact factor [102], international journals [117], and book chapters [116], [114].

G. Results in Decision Making

This section reveals the preliminary conclusions in the use of decision-making techniques inside the serious games field. First, all the included references in this section are outlined in Tables I–VI, according to the implemented AI method. They are classified, and a brief description of each study is outlined in previous sections, while main statistical outcomes regarding the decision-making field are summarized in this section.

1) AI Flagship: Table VII displays the number of publications segmented by the AI flagship type and decision-making method.

As is shown in Table VII, most of the articles revised in this section, 64.77%, fell under the category of "PEM—gameplay" (57 out of 88).

The remaining 31 studies were divided between the "PEM—objective," "procedural content generation," and "game data mining" categories.

Nine articles remained uncategorized as regards the AI flagship, while none was labeled under the "PEM—subjective" field.

2) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: Table VIII displays the number of publications segmented by the serious games market and decision-making method. As is displayed in Table VIII, the markets with the highest number of articles in their category are education (34.09%) and health (28.41%). Decision trees algorithms were the most used in health, education, and business markets. Fuzzy logic and Markov systems were also popular in health, education, and social change.
b) Serious games purpose: Table IX displays the number of publications according to the serious games purpose and decision-making method. Edugames and training are the categories with the highest number of labeled articles, with 42.05% and 36.36% of the included articles in each category, respectively. Regarding the purpose,

TABLE IX
SERIOUS GAMES MARKET: DECISION-MAKING TRENDS

Technique	N	Health	Edugame	Training	Activism	Uncat.
Decision Trees	27	4	7	13	2	1
Fuzzy Logic	16	3	7	6	0	0
Markov Systems	10	3	7	0	0	0
Goal Oriented Behavior	6	0	1	1	0	4
Rule-based Systems	10	0	7	3	0	0
Finite-State Machines	19	1	8	9	0	1
Total:	88	11	37	32	2	6
Percentage:	100	12.50%	42.05%	36.36%	2.27%	6.82%

TABLE X
PLATFORM/DELIVERY: DECISION-MAKING TRENDS

Technique	N	PC	Mobile/Tablet	Online	Other
Decision Trees	27	19	3	5	0
Fuzzy Logic	16	13	0	3	0
Markov Systems	10	9	0	1	0
Goal Oriented Behavior	6	6	0	0	0
Rule-based Systems	10	7	2	1	0
Finite-State Machines	19	17	1	1	0
Total:	88	71	6	11	0
Percentage:	100	80.68%	6.82%	12.50%	0.00%

TABLE XI
PROJECT TYPE: DECISION-MAKING TRENDS

Technique	N	Development	Framework	Other
Decision Trees	27	20	7	0
Fuzzy Logic	16	13	1	2
Markov Systems	10	6	3	1
Goal Oriented Behavior	6	1	5	0
Rule-based Systems	10	7	3	0
Finite-State Machines	19	16	0	3
Total:	88	63	19	6
Percentage:	100	71.59%	21.59%	6.82%

several algorithms were balanced used in the edugame segment: decision trees, fuzzy logic, Markov systems, rule-based systems, and finite-state machines. In training, finite-state machines and decision trees were used the most. The remaining segments were balanced.

c) Platform/delivery: Table X displays the number of publications according to the platform/delivery and decision-making method. The vast majority of the reviewed articles, 80.68%, were developed for PC. The second category with the highest number of references is online serious games, and the last mobile devices.

d) Project type: Table XI displays the number of publications segmented by the platform/delivery and decision-making method. Of the 88 available studies, 63 of them were concerned with new developments of serious games, while 19 were classified as frameworks. Only under the category of "goal-oriented behaviors' was the number of articles in frameworks higher than the number on new developments.

3) Sample of Participants: Of the 88 articles screened, 39 were tested in one way or another while 49 remained untested. Thus, 39 out of 88 articles did perform some kind of a user test with real participants, or, in the case of frameworks, did test their approach in a real context. The remaining 49 did not provide further information about any testing procedure, and were focused on the system's architecture, implementation, and design.

TABLE XII
PUBLICATION TYPE: DECISION-MAKING TRENDS

Technique	N	Type I	Type II	Type III	Type IV
Decision Trees	27	7	8	8	4
Fuzzy Logic	16	5	1	9	1
Markov Systems	10	2	1	5	2
Goal Oriented Behavior	6	1	0	5	0
Rule-based Systems	10	0	2	8	0
Finite-State Machines	19	1	1	15	2
Total:	88	16	13	50	9
Percentage:	100	18.18%	14.77%	56.82%	10.23%

4) Publication Type: Table XII displays the number of publications according to the publishing channel and decision-making method. Half of the revised articles were available through international conferences, workshops, and symposia. The remaining articles were more or less balanced in the number between the remaining three categories: international journals with impact factor, international journals, and chapters in books.

IV. MACHINE LEARNING

A system learns from an experience when it improves in the carrying out of a determined task, optimizing its performance. In the serious games area, this learning from experience is applied to the patterns of the users themselves, and also employed in the optimization of the behavior of NPCs and the agents of play, providing them with greater realism.

The intrinsic problem of algorithms of learning in the games field in general and of serious games in particular is the amount of usage time required to generate an effective learning system [119].

Below is a summary of the technical literature dealing with the most used techniques in this application theme.

A. Naive Bayes Classifier

Naive Bayes classifiers constitute a supervised classification and prediction technique based on the Bayes theorem. It is a learning and prediction technique based on storing a series of attribute–class pairs in a contingency table. All the attributes that have a class are independent from each other. New attributes are incorporated into one class or other according to the probability they have of belonging to one or other class [20].

Reviewing the literature concerning this technique, 13 articles were found. They were categorized as regards the characteristics outlined in Section II. Refer to Table XIII for a complete list of coded articles in this section.

1) AI Flagship: Nine out of the 13 articles included in this section fell into the "PEM—gameplay based" category. For example, Muñoz et al. developed a serious game for teaching physics to engineering students. A naïve Bayes classifier was used to adapt the gameplay based on users' performance [68].

Two articles were classified as "PEM—objective." An EEG device was used in one of them for the objective measurement

TABLE XIII
NAIVE BAYES CLASSIFIER AND SERIOUS GAMES: CODED ARTICLES

Authors	Country	Year	AI Flagship	AI Usage	Type	Platform	SG Market	SG Purpose	Participants				Publication*	Reference
									Total	Males	Females	Age		
Tseng and Wu	TW	2014	PEM - Objective	Classify Users	Development	PC (w/ online server)	Health	Exergame	85	36	49	55 - 85	Type II	(125)
Feldman *et al.*	AR	2014	PEM - Gameplay	Classify users	Framework	PC	–	–	47	–	–	University Students	Type I	(126)
Husain et al	MY	2013	Game Data Mining	Classify Users	Development	Web-Mobile	Health	Edugame	15 (Questionnaires) 30 (Children Persuasive Module)	– –	– –	26 - 48 –	Type III	(121)
Mori *et al.*	IT	2013	PEM - Gameplay	Interaction	Framework	PC	–	–	Developed a game to test the aproach of conversational agents in SG in a real context				Type II	(18)
Sabourin *et al.*	US	2013	PEM - Gameplay	Gameflow	Development	PC	Educational	Edugames	260	129	131	13.4 (SD = 0.57)	Type II	(25)
Keshtkar *et al.*	US	2012	PEM - Gameplay	Classify users	Development	PC	Business	Edugames	Tested over dataset with 83% accuracy				Type III	(123)
Nor Wan *et al.*	MY	2012	PEM - Gameplay	Classify users	Development	PC	Health	Health	31	10	21	over 65	Type III	(127)
Weichselbraun *et al.*	CH	2011	Game Data Mining	Assess users	Framework	–	–	–	Tested upon Sentiment Quiz, a web-based social verification game for sentiment detection.				Type III	(122)
Derbali *et al.*	CA	2011	PEM - Objective	Classify Users	Study	–	–	–	33	22	11	26.7 (SD 4.1)	Type III	(120)
Morgan *et al.*	US	2011	PEM - Gameplay	Classify users	Development	PC	Business	Edugames	21	–	–	High School	Type III	(128)
Muñoz *et al.*	IE	2010	PEM - Gameplay	Adapt gameplay	Development	PC	Educational	Edugames	28	–	–	University Students	Type III	(68)
Vaassen and Daelemans	NL	2010	PEM - Gameplay	Classifiy users	Development	PC	Business	Training	339 Dutch sentences				Type III	(124)
Rowe *et al.*	US	2009	PEM - Gameplay	Classifiy users	Development	PC	Educational	Edugame	59	–	–	Undergrad.	Type III	(129)

*(a) Type I: International journals with impact factor; (b) Type II: International journals; (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books.

TABLE XIV
ARTIFICIAL NEURAL NETWORKS AND SERIOUS GAMES: CODED ARTICLES

Authors	Country	Year	AI Flagship	AI Usage	Type	Platform	SG Market	SG Purpose	Participants				Publication*	Reference
									Total	Males	Females	Age		
Lamb *et al.*	US	2014	Game Data Mining	Gather user info	Study	PC	Educational	Edugame	–	–	–	–	Type I	(133)
Zhan *et al.*	US	2014	PEM - Objective	Gameflow	Development	PC	Health	Training	7	–	–	13 - 17	Type III	(130)
Gigliotta *et al.*	IT	2014	PEM - Gameplay	Gameflow	Study	PC	Educational	Edugame	Analyse different serious games				Type IV	(140)
Miglino *et al.*	IT	2012	PEM - Gameplay	Gameflow	Study	PC	Educational	Edugame	Analyse different serious games				Type III	(139)
Syufagi *et al.*	ID	2012	PEM - Gameplay	Classify users	Development	PC	Educational	Edugames	33	18	15	16 - 19	Type II	(134; 141; 142)
Otis *et al.*	CA	2012	PEM - Objective	Evaluate users	Development	PC	Health	Health	1	1	0	–	Type III	(131)
Grappiolo *et al.*	DK	2011	PEM - Gameplay	Gameflow	Development	PC	Culture and activism	Training	6 (Pilot study)	1	5	19 - 58	Type III	(136)
Puzenat and Verlut	FR	2010	PEM - Objective	Evaluate users state	Framework	PC	Health	Health	36	–	–	2 - 8	Type III	(132)
Arrabales *et al.*	ES	2009	PEM - Gameplay	Gameflow	Framework	PC + Bots	–	–	–	–	–	–	Type III	(138)
Rebolled-Mendez *et al.*	GB	2009	PEM - Gameplay	NPC Behaviour	Framework	PC	Educational	Edugames	–	–	–	–	Type III	(85)
Hildmann *et al.*	GB	2008	PEM - Gameplay	Gameflow	Development	Mobile	Educational	Training	–	–	–	–	Type III	(137)
Mills and Dalgarno	AU	2007	PEM - Gameplay	Evaluate users behavior	Development	PC	Educational	Edugame	Small pilot-test group				Type III	(135)

*(a) Type I: International journals with impact factor; (b) Type II: International journals; (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books.

of determining the risk of developmental problems among users [120].

The remaining articles were classified under the "game data mining" label as regards the AI flagship. The serious game *MyHealthyKids* made use of naïve Bayes to predict, based on the information gathered during the gameplay, whether a child is prone to be obese [121].

2) AI Usage: The majority of the included articles in this section used the naïve Bayes classifier to analyze users' gameplay and classify them as regards their performance.

The remaining four articles used naïve Bayes to assess the users [122], adapt the gameflow [25], [68], and analyze players' interaction [18].

3) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: Reviewed articles were quasi-balanced as regards the serious games market they belong to. Three articles out of 13 were labeled under health field, and three were classified both under education and under business field. The remaining four were unclassified as regards the serious games market they belong to.
b) Serious games purpose: Articles included in this section were classified as follows: Six articles were under the edugame category; another two were training games. The remaining four were unclassified.
c) Platform/delivery: Ten out of the 13 reviewed articles were developed for PC, while one was a web-mobile development and the remaining two were studies with no specified platform/delivery.
d) Project type: Nine of the reviewed articles were new development of serious games while three were framework designs and one was a study about the implications of motivation and attention during gameplay.

4) Sample of Participants: All the articles included in this section were tested in one way or another. Nine articles were tested with real participants. Two papers were tested over real data sets [123], [124]. The remaining two articles were tested upon an existing development, so as to test their approach in real serious games [18], [122].

5) Publication Type: Publication channels were segmented as follows: one article was published in an international journal with impact factor, three papers appeared in international journals, while other five were published as book chapters and in international conferences, workshops, and symposia, respectively.

B. Artificial Neural Networks

Artificial neural networks constitute a paradigm of learning. ANNs are composed of a set of "neurons" or states which are defined by a set of relevant features. These systems receive a group of inputs and generate a specific output. The connections between neurons are associated with a determined probabilistic weight, which gives knowledge to the system. ANNs emulate human brain behavior [20].

Twelve articles described research that employed artificial neural networks and could be analyzed further and coded following the categories outlined in Section II. Refer to Table XIV for a complete list of coded articles in this section.

1) AI Flagship: The majority of reviewed articles in this section, eight out of 12, were labeled under the "PEM—gameplay" category as regards their AI flagship.

TABLE XV
CASE-BASED REASONING AND SERIOUS GAMES: CODED ARTICLES

Authors	Country	Year	AI Flagship	AI Usage	Type	Platform	SG Market	SG Purpose	Participants				Publication*	Reference
									Total	Males	Females	Age		
Hulpus *et al.*	IE	2014	PEM - Gameplay	Gameflow	Framework	PC	Educational	Edugame	–	–	–	–	Type IV	(147)
Forsyth *et al.*	US	2013	PEM - Gameplay	Gameflow	Development	PC	Educational	Edugame	81	–	–	Undergraduate college students.	Type IV	(149)
Triki *et al.*	TN	2013	PEM - Gameplay	–	Model	Online	Social Change	Training	–	–	–	–	Type III	(146)
Tobail *et al.*	IE	2012	PEM - Gameplay	Gameflow	Framework	Online	Business	Training	–	–	–	–	Type III	(151)
Floryan & Woolf	US	2011	PEM - Gameplay	Gameflow	Development	PC	Educational	Edugame	Pilot study with students				Type III	(148)
Lopes & Bidarra	NL	2011	PEM - Gameplay	Gameflow	Framework	PC	–	–	–	–	–	–	Type III	(152)
Tobail *et al.*	IE	2011	Game Data Mining	Evaluate users' responses	Framework	Online	Business	Training	–	–	–	–	Type III	(144)
Hulpus *et al.*	IE	2010	PEM - Gameplay	Gameflow	Game Engine	PC	Business	Edugame	–	–	–	–	Type IV	(153)
McKenzie & McCalla	CA	2009	PEM - Gameplay	Gameflow	Development	Online	Culture and activism	Training	–	–	–	–	Type III	(145)
Chiann-Ru	TW	2006	PEM - Gameplay	Gameflow	Development	Online	Educational	Edugame	10	5	5	Undergraduate students	Type III	(150)

*(a) Type I: International journals with impact factor; (b) Type II: International journals; (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books.

Three articles took different measurements of players' actions on input devices such as eyetracker, motion capturing sensors, or even joysticks while playing [130]–[132] They were under the "PEM—objective" category.

The remaining article was developed as a game data mining system. It was a cognitive diagnostics tool for serious educational games [133].

2) AI Usage: Six articles were focused on altering gameflow based on the result of an implemented artificial neural network.

One framework [132], one study [133], and three developments [134], [135], [131] were focused on user evaluation and classification.

The remaining article made use of artificial neural networks for controlling NPC behaviors [85].

3) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: Seven articles fell under educational market. Three were under health field [130], [131], [132], and one belonged to culture and activism [136]. The remaining study was uncategorized.
b) Serious games purpose: Six articles were classified as edugames, three were under training [136], [137], [130], and two were health related [131], [132]. The remaining article was uncategorized.
c) Platform/delivery: All but one of the included studies were developed for PC. The remaining article described a system developed for mobile devices [137].
d) Project type: Six articles were new developments of serious games, while three studies were framework designs and implementations [138], [85], [132]. The remaining three were research studies [139], [140], [133].

4) Sample of Participants: Four articles did not give any further information about their testing procedures.

Three studies were pilot tested; one of them gave the number of participants [136] while another only refers to being tested with a small pilot group [135]. The last pilot study performed the testing procedure with one single user [131].

Four articles gave age of the participants, but gender was only given in two of them [136], [134].

Two out of the three included studies applied their findings to the analysis of existing serious games [139], [140].

5) Publication Type: The majority of articles were published in international conferences, workshops, and symposia.

The remaining three articles were published in an international journal with impact factor [133], in an international journal [134], and as a book chapter [140].

C. Case-Based Reasoning

Case-based reasoning is the technique based on the ability or capacity to solve or determine the outputs of the system based on the solutions adopted before. Systems implementing this technique start with a known training data set from which a set of knowledge is drawn for future references.

Case-based reasoning techniques are applied in the field of interactive serious games mainly when they are related to automatic customizations of its contents based on user interaction. These techniques provide systems with an efficient way of learning from users, providing them with customized and personal experiences [143].

Ten articles were found in this section that fulfilled the inclusion criteria for this review in the category of case-based reasoning. Refer to Table XV for a complete list of coded articles in this section.

1) AI Flagship: All but one of the included references fell under the "PEM—gameplay" category.

The remaining study was oriented toward "game data mining." It was an automobile supply chain simulation game, where users' actions and decisions were knowledge inputs to the case-based reasoning system, improving its response for future situations [144].

2) AI Usage: Eight articles implemented case-based reasoning techniques for adapting the gameflow, providing final users with personalized gaming experiences.

One of the included references used case-based reasoning for users' responses evaluation [144].

The remaining article was uncategorized as regards its AI usage.

3) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: Four articles were labeled under the educational field and three articles were labeled under business. Remaining three articles were classified as culture and activism [145], social change [146], and uncategorized, respectively.
b) Serious games purpose: Five articles were labeled for having an edugame purpose and four articles were placed in

TABLE XVI
SUPPORT VECTOR MACHINES AND SERIOUS GAMES: CODED ARTICLES

Authors	Country	Year	AI Flagship	AI Usage	Type	Platform	SG Market	SG Purpose	Participants				Publication*	Reference
									Total	Males	Females	Age		
Bernardini *et al.*	UK	2013	PEM - Objective	Classify users	Development	PC	Health	Training	19	–	–	–	Type I + Type III	(157; 158)
Berta *et al.*	IT	2013	PEM - Objective	Classify users	Framework	PC	–	–	22	17	5	Engineering, Masters and PhD students.	Type I	(156)
Parsons & Reinebold	US	2012	PEM - Objective	Evaluate users	Framework	PC	Military	Health	337	–	–	21 - 36	Type I	(155)
Ahn & Lee	KR	2011	PEM - Objective	Classify users	Game System	PC	Health	Health	10	–	–	–	Type III	(154)
Raybourn *et al.*	US	2010	PEM - Gameplay	Predict users' behaviours	Development	PC	Military	Edugame	78	–	–	–	Type III	(159)

*(a) Type I: International journals with impact factor; (b) Type II: International journals; (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books.

the training category. The remaining article was uncategorized as regards its purpose.

c) Platform/delivery: Five of the developments and framework studied were intended for PC, while the remaining four were designed for online use.

d) Project type: Four articles were new serious games developments, while other four were frameworks for the creation of new games. The remaining two articles were game engine implementation [147] and serious games design model [146].

4) Sample of Participants: Three articles did test their developments with real participants. The *Rashi Game* was tested in a pilot study with students [148]. No further information was given about the number of participants, age, or gender. Operation ARA creators referred to having tested their development with a group of 81 undergraduate college students [149]. The serious game *The Life of Moses* was tested with a small gender-balanced group of undergraduate students [150].

5) Publication Type: Seven articles were published in international conferences, workshops, and symposia, while the remaining three were published as book chapters.

D. Support Vector Machines

Support vector machines (SVMs) are a set of supervised algorithms focused on data analysis and pattern recognition. Data are clustered using hyperplanes in a multidimensional space that maximizes separation between classes. This clustering is based on decision boundaries.

Six articles were found in this section fulfilling the inclusion criteria of the SVM category. Refer to Table XVI for a complete list of coded articles in this section.

1) AI Flagship: Five articles fell into the category of "PEM—objective" as regards their AI flagship. They made use of sensors, such as EEG [154]–[156] or eyetracker [157], [158], for recording biological data while playing. The remaining article was labeled as "PEM—gameplay" [159].

2) AI Usage: The included articles were focused on predicting [159], evaluating [155], or classifying [154], [156] users' behaviors while playing. One article used SVMs for controlling NPC behaviors [160].

3) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: Three articles were classified as belonging to health field [154], [158], [160]; the other two were under military field [159], [155]. The remaining article was uncategorized.

b) Serious games purpose: Considering the purpose of the serious game, two articles were labeled for having both health-related purposes [154], [155] and training purposes [160], [158]. One article was classified for being an edugame [159], and the last one was uncategorized as regards its final purpose [156].

c) Platform/delivery: All the included articles were designed and/or developed for PC.

d) Project type: Two articles were new developments of serious games [158], [159], while other three were new framework designs [155], [156], [160]. The remaining article was a game system implementation [154].

4) Sample of Participants: All the articles were tested with real participants. Three of them gave further information about gender segmentation [156], [160] and age of the participants [155], [160].

5) Publication Type: Three articles were published in international journals with impact factor, while other three were made available through international conferences, workshops, and symposia.

E. Results in Learning

This section exposes preliminary conclusions in the use of machine learning techniques inside the serious games field. First, all the included references in this section are outlined in Tables XIII–XVI according to the implemented AI method. They are classified, and a brief description of each study is outlined in previous sections while main statistical outcomes regarding the decision-making field are summarized in this section.

1) AI Flagship: Table XVII displays the number of publications segmented by the AI-flagship-type and machine-learning method.

As is shown in Table XVII, most of the articles revised in this section, 65.85%, fell under the category of "PEM—gameplay" (27 out of 41).

The remaining 14 studies were divided between the "PEM—objective" (ten out of 41) and "game data mining" (four out of 41) categories.

None of the reviewed articles in Section IV was labeled under "PEM—subjective" or under "procedural content generation" flagships.

2) Categorization of Games: The articles were classified according to the following features.

a) Serious games market: Table XVIII displays the number of publications segmented by the serious games

TABLE XVII
AI FLAGSHIP: MACHINE-LEARNING TRENDS

Technique	N	Player Experience Modeling			Procedural	Game	Uncat.
		Subjective	Objective	Gameplay	Content Generation	Data Mining	
Näive Bayes Classifier	13	0	2	9	0	2	0
Artificial Neural Networks	12	0	3	8	0	1	0
Case-Based Reasoning	10	0	0	9	0	1	0
Support Vector Machines	6	0	5	1	0	0	0
Total:	41	0	10	27	0	4	0
Percentage:	100	0.00%	24.39%	65.85%	0.00%	9.76%	0.00%

TABLE XVIII
SERIOUS GAMES MARKET: MACHINE-LEARNING TRENDS

Technique	N	Health	Education	Business	Culture and Activism	Social Change	Political	Military	Uncat.
Näive Bayes Classifier	13	3	3	3	0	0	0	0	4
Artificial Neural Networks	12	3	7	0	1	0	0	0	1
Case-Based Reasoning	10	0	4	3	1	1	0	0	1
Support Vector Machines	6	3	0	0	0	0	0	2	1
Total:	41	9	14	6	2	1	0	2	7
Percentage:	100	21.95%	34.15%	14.63%	4.88%	2.44%	0.00%	4.88%	17.07%

TABLE XIX
SERIOUS GAMES PURPOSE: MACHINE-LEARNING TRENDS

Technique	N	Health	Edugame	Training	Activism	Uncat.
Näive Bayes Classifier	13	1	6	2	0	4
Artificial Neural Networks	12	2	6	3	0	1
Case-Based Reasoning	10	0	5	4	0	1
Support Vector Machines	6	2	1	2	0	1
Total:	41	5	18	11	0	7
Percentage:	100%	12.20%	43.90%	26.83%	0.00%	17.07%

TABLE XX
PLATFORM/DELIVERY: MACHINE-LEARNING TRENDS

Technique	N	PC	Mobile / Tablet	Online	Other
Näive Bayes Classifier	13	10	1	0	2
Artificial Neural Networks	12	11	1	0	0
Case-Based Reasoning	10	5	0	5	0
Support Vector Machines	6	6	0	0	0
Total:	41	32	2	5	2
Percentage:	100%	78.05%	4.88%	12.20%	4.88%

TABLE XXI
PROJECT TYPE: MACHINE-LEARNING TRENDS

Technique	N	Development	Framework	Other
Näive Bayes Classifier	13	9	3	1
Artificial Neural Networks	12	6	3	3
Case-Based Reasoning	10	4	4	2
Support Vector Machines	6	2	3	1
Total:	41	21	13	7
Percentage:	100	51.22%	31.71%	17.07%

market and machine-learning method. As is displayed in Table XVIII, the market with the highest number of articles in its category is education (34.15%), followed by health market (21.95%) and business (14.63%). The reviewed algorithms are quite balanced in this section, however, artificial neural networks stand out in their use inside the education market.

b) Serious games purpose: Table XIX displays the number of publications segmented by the serious games purpose and machine-learning method. Edugames and training are the categories with the highest number of labeled articles, with 43.90% and 26.83% of the included articles in each category, respectively. In this section, 17.07% of the reviewed serious games were uncategorized as regards their purpose. None of the articles was labeled under the activism field.

c) Platform/delivery: Table XX displays the number of publications according to the platform/delivery and machine-learning method. The vast majority of the reviewed articles, 78.05%, were developed for PC. The second category with the highest number of references is online serious games developments (12.20%), and the last mobile devices or other platforms (4.88% each).

d) Project type: Table XXI displays the number of publications segmented by the platform/delivery and decision making method. Twenty one out of the 41 available articles were concerned with new developments of serious games, while 13 were classified as frameworks. The number of frameworks and developments are very balanced under the categories of case-based reasoning and SVMs.

3) Sample of Participants: Thirty out of 41 articles did perform some kind of a user test with real participants, or, in the case of frameworks, did test their approach in a real context. The remaining 11 did not provide further information about any testing procedure.

4) Publication Type: Table XXII displays the number of publications according to the publishing channel and machine-learning method: 60.98% of the included articles were made

TABLE XXII
PUBLICATION TYPE: MACHINE-LEARNING TRENDS

Technique	N	Type I	Type II	Type III	Type IV
Näive Bayes Classifier	13	1	3	5	4
Artificial Neural Networks	12	1	1	9	1
Case-Based Reasoning	10	0	0	7	3
Support Vector Machines	6	3	0	4	0
Total:	41	5	4	25	8
Percentage:	100%	12.20%	9.76%	60.98%	19.51%

*(a) Type I: International journals with impact factor; (b) Type II: International journals; (c) Type III: International conferences, workshops, and symposia; and (d) Type IV: Chapters in books.

available through international conferences, workshops, and symposia; 19.51% was published as chapters in books; 12.20% appeared in international journals with impact factor; the remaining 9.76% was published in international journals.

V. Discussion and Conclusion

The number and the distribution of papers identified using the search terms listed in this paper confirm the large and increasing interest in the serious games field related to artificial intelligent algorithms and techniques. Our inclusion criteria identified 129 papers providing evidence for the development and integration of some specific AI algorithms related to fields of decision making and machine learning.

The papers selected for this review were very diverse in terms of their area of research and application, market and purpose, and project and delivery type, reflecting the varied backgrounds of the researchers and their different interests in serious games. However, all of them have the AI field in common. This, together with the multifeature analysis performed in this paper, helped the authors to create a common analysis framework for organizing and comparing all the included studies.

The results are quite consistent between the two main sections of this paper, which may help to establish some trends regarding the use of decision-making and machine learning algorithms in serious games design and development.

A. Algorithms Used

Considering Section III, the number of articles included under the umbrella of decision trees is considerably higher than the number of studies found for the rest of algorithms. Decision trees are computationally undemanding, and have been found useful as components of intelligent systems [161].

However, in Section IV, the included number of articles was quite balanced between naïve Bayes classifiers, artificial neural networks, and case-based reasoning algorithms. SVM algorithms had the lower inclusion rate in Section IV. The vast majority of the SVM studies in this review were focused on classifying, evaluating, or predicting users' states and behaviors using biological sensors. SVMs are supervised classifiers that have been improved to successfully work with limited quantity and quality of training samples [162], which may help in their implementation with biological data.

B. AI Flagship

Some 65% of articles included in both Sections III and IV belong to the "PEM—gameplay" flagship. This is an interesting outcome since both of the reviewed sections produced the same result. According to Yannakakis, gameplay-based PEM is the less intrusive and most computationally efficient approach for games [19], which may be the reason for its high incidence in this review.

"PEM—subjective" flagship did not have representation in this review, which may be because the authors were more focused on algorithm-centered studies.

C. AI Usage

AI techniques were applied with a wide variety of final purposes for each article. The most common implementations were for altering the gameflow or for assessing/classifying users' state and behavior while playing. The production of intelligent serious games that dynamically adapt themselves to users' needs and performance have been proved to be efficient in terms of improvement comparisons [163].

D. Serious Games Market

Education and health markets were the most widespread markets considering the reviewed algorithms. No recent key figures were found regarding the serious games market analysis. However, the market study published by IDATE which ranges from 1952 to 2009 proved that serious games in most cases were designed for education [164].

E. Serious Games Purpose

Edugame-related purposes were the most employed purpose in this review. This may be because the use of serious games for learning purposes is already established [165].

F. Platform/Delivery

The vast majority of the articles included in both decision-making and machine learning categories were designed and/or developed for PC. Studies that involved online or mobile serious games were in discreet middle distance. Similar results were found by Connolly et al. in their review about computer and serious games [165].

However, in recent years, the number of smartphones sold to end users worldwide has increased sharply. In 2013, the number of smartphones sold to customers increased by 50% from 2011. This means that almost 20% of world's population owned a smart device. This figure is expected to grow to 34% by 2017 [166]. This increase in the use of portable devices connected to the Internet could mark a change in trends regarding serious games delivery platform.

G. Testing Procedure

Only about a half of all the articles included in this review, thus 69 out of 129, did perform some kind of a user test with real participants, or, in the case of frameworks, did test their approach in a real context. The serious games community is very fragmented, and creating a systematic procedure for validating the usability and penetration of serious games may be a challenge [167]. However, the authors consider that serious games are closely related to final users, so they need to be tested with real participants, so as to ensure their usability and effectiveness. Thus, available studies regarding the use of artificial intelligence in serious games may need to improve their testing procedures. Testing procedures in serious games need to be carefully designed, since multiple variables take part in them. Pretest and posttest assessment protocols may help in testing efficacy and efficiency in serious games and in their learning outcomes. Serious games also imply that they are, above all, games, so fun and engagement elements must be also ensured and tested [168].

It may also be useful to refine our working classification of outcomes, proposing a higher level classification for the testing procedure, thus, focusing on the appropriateness and adequacy of the employed methodology by analyzing and categorizing study design, sampling, and data collection methods. This higher level classification will help to understand the underlying testing procedures, providing the community with a better understanding of the testing protocols used in serious games design. Serious games that use AI techniques should also consider the performance of those algorithms in the final game. Intelligent games should be carefully designed and algorithms need to perfectly suit the final objectives of the game.

H. Publication Type

More than half of the articles included in this review were available through international conference workshops and symposia. Traditionally, there was a preference for conference publication in the field of computer science [169]. The articles included in this review were published in 56 different international conferences, workshops, and symposia. The conference with the higher number of publications in this category was VS-GAMES. Only eight out of these 56 conferences were specifically oriented to either games or serious games design and development. Nine out of the 56 conferences were indexed in the computer science conference rankings. Regarding journals, 21 papers were published in international journals with impact factor. These publications were distributed as follows: eight articles were found in Q1 journals, five article were found in Q2 journals, six articles were found in Q3 journals, and the remaining two articles were published in Q4 journals. These figures suggest a growing interest in the serious games field that goes beyond the specialized conferences.

The current study has extended our understanding in the trends and tendencies of the categorization of AI techniques inside the serious games field. It is important to determine whether our classification is the most useful way of characterizing the different outcomes. Although several aspects related to the serious games field and AI algorithms have been studied, there was some ambiguity about which category an outcome should be coded under. For example, in the case of AI flagships, sometimes "PEM—gameplay" overlaps with "game data mining," and how these are viewed depends upon the perspective of the reader. However, due to the number of references inside the "PEM—gameplay" field, this did not affect the final outcome of this trend analysis.

AI techniques offer significant potential in the development of serious games, enhancing the player experience in all the stages of its gaming experience. As has been reviewed in this paper, AI algorithms may help to improve several stages inside the serious games development.

1) Inner working of the game: Serious games are constantly moving closer to modern games development, following the same pattern with regard to AI techniques. Most modern games address three basic game-related needs when implementing intelligent algorithms: move characters, make decisions inside the gameflow, and think tactically [20]. These needs have also been found throughout this paper, where several articles made use of AI techniques for the inner workings of the game.
2) Personalized gaming experience: The design and development of adaptive intelligent serious games with content changes based on user interaction makes player experience, training, and education more customized. AI techniques provide systems with an efficient way of learning based on the users themselves, providing them with customized personal experiences, which may increase their potential effects [170].

In summary, AI techniques are not only not limited in the context of serious games but also they have a promising potential in the future of this area. The revised literature highlights the potential of intelligent serious games, and the wide range of possibilities they provide to researchers, professionals, and final users. The future of serious games will probably be closer to modern games development involving more AI algorithms, arts, and animations and ending with serious games that more resemble modern video games, engaging users and game professionals in their path.

I. Limitation

The current review has a number of limitations. As with all reviews, it was limited by the search terms used, the databases employed, and the time period selected. However, this review helps to contextualize the use of some mainstream artificial intelligence algorithms in the field of serious games, giving an overview of the trends and limitations over the last decade.

I. Conclusion

Finally, the authors consider that in recent years enough knowledge has been gathered to create new intelligent serious games to consider not only the final aim but also the technologies and techniques used to provide players with a nearly real experience. This new age of serious games is very close to the world of video games, and they generate new solutions completely adapted to their target audience. However, researchers may need to improve their methodology for testing developed serious games, so as to ensure they meet their final purposes. Moreover, the authors would like to encourage other researchers to use this paper in other AI-specific techniques and/or addressing new AI-related features, to extend this state of the art in the field of serious games, creating a knowledge hub for researchers in the area.

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REFERENCES

[1] C. C. Abt, *Serious Games*, Lanham, MD, USA: Univ. Press Amer., 1987.
[2] T. Dumbleton and J. Kirriemuir, "13 digital games and education," *Understanding Digital Games*, pp. 223, 2006.
[3] U. Ritterfeld, M. Cody, and P. Vorderer, "Serious games: Mechanisms and effects," *Routledge*, 2009.
[4] C. Girard, J. Ecalle, and A. Magnan, "Serious games as new educational tools: How effective are they? A meta-analysis of recent studies," *J. Comput. Assisted Learn.*, vol. 29, no. 3, pp. 207–219, 2013.
[5] J. P. Gee, "What video games have to teach us about learning and literacy," *Comput. Entertain.*, vol. 1, no. 1, pp. 20–20, 2003.
[6] F. L. Greitzer, O. A. Kuchar, and K. Huston, "Cognitive science implications for enhancing training effectiveness in a serious gaming context," *J. Educ. Resources Comput.*, vol. 7, no. 3, pp. 2, 2007.
[7] F. Bellotti, B. Kapralos, K. Lee, P. Moreno-Ger, and R. Berta, "Assessment in and of serious games: An overview," *Adv. Human-Comput. Interaction*, vol. 2013, pp. 1, 2013.
[8] B. Sawyer and P. Smith, "Serious games taxonomy," Slides from the Serious Games Summit at the Game Developers Conference, 2008.
[9] D. R. Michael and S. L. Chen, *Serious Games: Games That Educate, Train, and Inform*, Muska & Lipman/Premier-Trade, USA, 2005.
[10] M. Zyda, "From visual simulation to virtual reality to games," *Computer*, vol. 38, no. 9, pp. 25–32, 2005.
[11] J. Alvarez and L. Michaud, "Serious games. Advergaming, edugaming, training and more," in *Proc. IDATE*, 2008.
[12] R. Ratan and U. Ritterfeld, "Classifying serious games," *Serious Games: Mechanisms and Effects*, pp. 10–24, 2009.
[13] A. J. Stapleton, "Serious games: Serious opportunities," in *Proc. Austral. Game Develop. Conf.*, Melbourne, Australia: 2004.
[14] L. Michaud and J. Alvarez, *Serious Games: Advergaming, Edugaming, Training*, Paris, France: IDATE, 2008.
[15] B. P. Bergeron, *Developing Serious Games*, London, U.K., Charles River Media Hingham, 2006.
[16] J. S. Breuer and G. Bente, "Why so serious? On the relation of serious games and learning," *Eludamos. J. Comput. Game Culture*, vol. 4, no. 1, pp. 7–24, 2010.
[17] D. Djaouti, J. Alvarez, and J.-P. Jessel, "Classifying serious games: The g/p/s model," *Handbook of Research on Improving Learning and Motivation Through Educational Games: Multidisciplinary Approaches*, 2011, pp. 118–136.
[18] D. Mori, R. Berta, A. De Gloria, V. Fiore, and L. Magnani, "An easy to author dialogue management system for serious games," *J. Comput. Cultural Heritage*, vol. 6, no. 2, pp. 10, 2013.
[19] G. N. Yannakakis, "Game AI revisited," in *Proc. 9th Conf. Comput. Front.*, 2012, pp. 285–292.
[20] I. Millington and J. D. Funge, *Artificial Intelligence for Games*, London, U.K.: Taylor & Francis, 2009.
[21] A. Sordoni *et al.*, "Design of a participatory decision making agent architecture based on argumentation and influence function–application to a serious game about biodiversity conservation," *RAIRO-Oper. Res.*, vol. 44, no. 4, pp. 269–283, 2010.
[22] D. Cantwell, D. O. Broin, R. Palmer, and G. Doyle, "Motivating elderly people to exercise using a social collaborative exergame with adaptive difficulty," 2012.
[23] R. Costa, I. Mendonca, and D. Souza, "Exploring the intelligent agents for controlling user navigation in 3D games for cognitive stimulation," in *Proc. 8th Int. Conf. Disability Virtual Reality Assoc. Technol.*, 2010, vol. 1, pp. 1–6.
[24] F. Keshtkar, C. Burkett, H. Li, and A. C. Graesser, "Using data mining techniques to detect the personality of players in an educational game," *Educational Data Mining*, New York, NY, USA: Springer-Verlag, 2014, pp. 125–150.
[25] J. L. Sabourin, L. R. Shores, B. W. Mott, and J. C. Lester, "Understanding and predicting student self-regulated learning strategies in game-based learning environments," *Int. J. Artif. Intell. Educ.*, vol. 23, no. 14, pp. 94–114, 2013.
[26] B. Horan and M. Gardner, "+ spaces: Serious games for role-playing government policies," *Understanding Learning in Virtual Worlds*, New York, NY, USA: Springer-Verlag, 2013, pp. 101–116.
[27] P. Petridis *et al.*, "The Herbert virtual museum," *J. Electr. Comput. Eng.*, vol. 2013, 2013.
[28] A. M. Hussaan, K. Sehaba, and A. Mille, "Helping children with cognitive disabilities through serious games: Project CLES," in *Proc. 13th Int. ACM SIGACCESS Conf. Comput. Accessibility*, 2011, pp. 251–252.
[29] S. Tang *et al.*, "Towards a domain specific modelling language for serious game design," in *Proc. 6th Int. Game Design Technol. Workshop*, Liverpool, U.K., 2008, pp. 43–52.
[30] M. Frutos-Pascual, B. G. Zapirain, and A. M. Zorrilla, "Adaptive tele-therapies based on serious games for health for people with time-management and organisational problems: Preliminary results," *Int. J. Environ. Res. Public Health*, vol. 11, no. 1, pp. 749–772, 2014.
[31] F. E. Santos, A. P. Bastos, L. C. Andrade, K. Revoredo, and P. Mattos, "Assessment of ADHD through a computer game: An experiment with a sample of students," in *Proc. 3rd Int. Conf. Games Virtual Worlds Serious Appl.*, 2011, pp. 104–111.
[32] J. Qin, Y.-P. Chui, W.-M. Pang, K.-S. Choi, and P.-A. Heng, "Learning blood management in orthopedic surgery through gameplay," *IEEE Comput. Graph. Appl.*, vol. 30, no. 2, pp. 45–57, 2010.
[33] R. Haworth, S. S. T. Bostani, and K. Sedig, "Visualizing decision trees in games to support children's analytic reasoning: Any negative effects on gameplay?," *Int. J. Comput. Games Technol.*, vol. 2010, pp. 3, 2010.
[34] B. M. Good *et al.*, "The cure: Making a game of gene selection for breast cancer survival prediction," 2014, Online. [Available]: https://arxiv.org/abs/1402.3632
[35] D. Parsons, K. Petrova, and H. Ryu, "Mobile gaming—A serious business!," in *Proc. IEEE 7th Int. Conf. Wireless Mobile Ubiquitous Technol. Educ.*, 2012, pp. 17–24.
[36] Z. Chiang, "The pricing strategy in chain store operation simulation system based on decision tree," in *Proc. 4th Int. Joint Conf. Comput. Sci. Optim.*, 2011, pp. 392–395.
[37] J. Lilly and M. Warnes, "Designing mobile games for learning—The MGBL approach," *Serious Games on the Move*, O. Petrovic, A. Brand, Eds., New York, NY, USA: Springer-Verlag, 2009, pp. 3–25.
[38] T. Rijcken, J. Stijnen, and N. Slootjes, "Simdelta: Inquiry into an internet-based interactive model for water infrastructure development in The Netherlands," *Water*, vol. 4, no. 2, pp. 295–320, 2012.
[39] J. M. Kim *et al.*, "Bilat: A game-based environment for practicing negotiation in a cultural context," *Int. J. Artif. Intell. Educ.*, vol. 19, no. 3, pp. 289–308, 2009.
[40] F.-H. Tsai, K.-C. Yu, and H.-S. Hsiao, "Exploring the factors influencing learning effectiveness in digital game-based learning," *Educ. Technol. Soc.*, vol. 15, no. 3, pp. 240–250, 2012.
[41] E. Castro-Sanchez, E. Charani, L. Moore, M. Gharbi, and A. Holmes, "Taking antimicrobial stewardship initiatives to the next level: Development of a serious prescribing game for acute care," *Int. J. Infectious Diseases*, pp. 46–47, 2014.
[42] C. F. Lin, Y.-C. Yeh, Y. H. Hung, and R. I. Chang, "Data mining for providing a personalized learning path in creativity: An application of decision trees," *Comput. Educ.*, vol. 68, pp. 199–210, 2013.
[43] E. D. van der Spek, P. Wouters, and H. van Oostendorp, "Code red: Triage or cognition-based design rules enhancing decision making training in a game environment," *Brit. J. Educ. Technol.*, vol. 42, no. 3, pp. 441–455, 2011.
[44] S. Moya, S. Grau, and D. Tost, "The wise cursor: Assisted selection in 3D serious games," *Visual Comput.*, vol. 29, no. 68, pp. 795–804, 2013.
[45] A. M. Hussaan and K. Sehaba, "Generator of adaptive learning scenarios: Design and evaluation in the project CLES," in *Proc. 21st Century Learn. 21st Century Skills*, 2012, pp. 166–179.
[46] J. Goulding, W. Nadim, P. Petridis, and M. Alshawi, "Construction industry offsite production: A virtual reality interactive training environment prototype," *Adv. Eng. Inf.*, vol. 26, no. 1, pp. 103–116, 2012.
[47] I. Ghergulescu and C. H. Muntean, "Learner motivation assessment with e-adventure game platform," in *Proc. World Conf. E-Learn. Corporate Govern. Healthcare Higher Educ.*, 2011, pp. 1212–1221.

[48] A. C. Vidani and L. Chittaro, "Using a task modeling formalism in the design of serious games for emergency medical procedures," in *Proc. IEEE Conf. Games Virtual Worlds Serious Appl.*, 2009, pp. 95–102.

[49] F. Bellotti, R. Berta, A. De Gloria, and L. Primavera, "Adaptive experience engine for serious games," *IEEE Trans. Comput. Intell. AI Games*, vol. 1, no. 4, pp. 264–280, 2009.

[50] M. Fazzolari, R. Alcalá, Y. Nojima, H. Ishibuchi, and F. Herrera, "A review of the application of multiobjective evolutionary fuzzy systems: Current status and further directions," *IEEE Trans. Fuzzy Syst.*, vol. 21, no. 1, pp. 45–65, 2013.

[51] D. Balas, C. Brom, A. Abonyi, and J. Gemrot, "Hierarchical petri nets for story plots featuring virtual humans," in *Proc. AIIDE*, 2008.

[52] A. Karime, M. Eid, J. M. Alja'am, A. Saddik, and W. Gueaieb, "A fuzzy-based adaptive rehabilitation framework for home-based wrist training," *IEEE Trans. Instrum. Meas.*, vol. 63, no. 1, pp. 135–144, 2014.

[53] M. Pirovano, R. Mainetti, G. Baud-Bovy, P. L. Lanzi, and N. A. Borghese, "Self-adaptive games for rehabilitation at home," in *Proc. IEEE Conf. Comput. Intell. Games*, 2012, pp. 179–186.

[54] M. Farhangian, M. K. Purvis, M. Purvis, and B. T. R. Savarimuthu, "Modelling the effects of personality and temperament in small teams," *Coordination, Organizations, Institutions, and Norms in Agent Systems IX*, Berlin, Germany: Springer-Verlag, 2014, pp. 25–41.

[55] F. de Oliveira *et al.*, "ARVET and SAPTEPT: A virtual environment and a system supported by fuzzy logic in virtual reality exposure therapy for PTSD patients," in *Proc. 12th Int. Conf. Comput. Sci. Appl.*, 2012.

[56] F. Imbeault, B. Bouchard, and A. Bouzouane, "Serious games in cognitive training for Alzheimer's patients," in *Proc. IEEE 1st Int. Conf. Serious Games Appl. Health*, 2011, pp. 1–8.

[57] Y. Cai, C. Miao, A.-H. Tan, Z. Shen, and B. Li, "Creating an immersive game world with evolutionary fuzzy cognitive maps," *IEEE Comput. Graph. Appl.*, vol. 30, no. 2, pp. 58–70, 2010.

[58] I. A. Buditjahjanto and H. Miyauchi, "An intelligent decision support based on a subtractive clustering and fuzzy inference system for multiobjective optimization problem in serious game," *Int. J. Inf. Technol. Decision Making*, vol. 10, no. 05, pp. 793–810, 2011.

[59] D. D. Djordjevich *et al.*, "Preparing for the aftermath: Using emotional agents in game-based training for disaster response," in *Proc. IEEE Symp. Comput. Intell. Games*, 2008, pp. 266–275.

[60] M. Pirovano and P. L. Lanzi, "Fuzzy tactics: A scripting game that leverages fuzzy logic as an engaging game mechanic," *Expert Syst. Appl.*, vol. 41, no. 13, pp. 6029–6038, 2014.

[61] D. Zaldivar *et al.*, "An educational fuzzy-based control platform using Lego robots," *Int. J. Electr. Eng. Educ.*, vol. 50, no. 2, pp. 157–171, 2013.

[62] Z. Shen *et al.*, "An emotional agent in virtual learning environment," *Trans. Edutainment*, IV, pp. 22–33, 2010.

[63] C. Oliveira, M. Cintra, and F. Mendes Neto, "Learning risk management in software projects with a serious game based on intelligent agents and fuzzy systems," in *Proc. 8th Conf. Eur. Soc. Fuzzy Logic Technol.*, 2013.

[64] I. S. Brasil *et al.*, "An intelligent agent-based virtual game for oil drilling operators training," in *Proc. IEEE XIII Symp. Virtual Reality*, 2011, pp. 9–17.

[65] I. S. Brasil *et al.*, "An intelligent and persistent browser-based game for oil drilling operators training," in *Proc. IEEE 1st Int. Conf. xSerious Games Appl. Health*, 2011, pp. 1–9.

[66] O. J. Petit dit Dariel, T. Raby, F. Ravaut, and M. Rothan-Tondeur, "Developing the serious games potential in nursing education," *Nurse Education Today*, 2013.

[67] C. Gardiner, *Stochastic Methods*, Berlin, Germany: Springer-Verlag, 1985.

[68] K. Muñoz, P. Mc Kevitt, T. Lunney, J. Noguez, and L. Neri, "Playphysics: An emotional games learning environment for teaching physics," 2010, pp. 400–411.

[69] L. Derbali, R. Ghali, and C. Frasson, "Assessing motivational strategies in serious games using hidden Markov models," in *Proc. 26th Int. FLAIRS Conf.*, 2013.

[70] P.-H. Su, Y.-B. Wang, T.-H. Yu, and L.-S. Lee, "A dialogue game framework with personalized training using reinforcement learning for computer-assisted language learning," in *Proc. IEEE Int. Conf. Acoust. Speech Signal Process.*, 2013, pp. 8213–8217.

[71] P.-H. Su, C.-H. Wu, and L.-S. Lee, "A recursive dialogue game for personalized computer-aided pronunciation training," *IEEE/ACM Trans. Audio Speech Lang. Process.*, vol. 23, pp. 127–141, 2014.

[72] A. N. Rafferty, M. Zaharia, and T. L. Griffiths, "Optimally designing games for cognitive science research," in *Proc. Annu. Meeting Cogn. Sci. Soc.*, 2012.

[73] A. Navarro-Newball *et al.*, "Talking to Teo: Video game supported speech therapy," *Entertain. Comput.*, vol. 5, no. 4, pp. 401–412, 2014.

[74] B. Bouchard, F. Imbeault, A. Bouzouane, and B.-A. J. Menelas, "Developing serious games specifically adapted to people suffering from Alzheimer," *Serious Games Development and Applications*, New York, NY, USA: Springer-Verlag, 2012, pp. 243–254.

[75] L. E. Sucar *et al.*, "Gesture therapy: An upper limb virtual reality-based motor rehabilitation platform," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 3, pp. 634–643, 2014.

[76] W. L. Johnson and A. Valente, "Tactical language and culture training systems: Using artificial intelligence to teach foreign languages and cultures," in *Proc. AAAI*, 2008, pp. 1632–1639.

[77] J. N. Neto, R. Silva, J. P. Neto, J. M. Pereira, and J. Fernandes, "Solis' curse-a cultural heritage game using voice interaction with a virtual agent," in *Proc. 3rd Int. Conf. Games Virtual Worlds Serious Appl.*, 2011, pp. 164–167.

[78] W. L. Johnson, N. Wang, and S. Wu, "Experience with serious games for learning foreign languages and cultures," in *Proc. SimTecT Conf.*, 2007.

[79] W. L. Johnson, "Serious use of a serious game for language learning," *Front. Artif. Intell. Appl.*, vol. 158, pp. 67, 2007.

[80] J. Orkin, "Goal oriented action planning," *CTAN*, 2010, Online. [Available]:http://web.media.mit.edu/jorkin/goap.html.

[81] J. Orkin, "Three states and a plan: The AI of fear," in *Proc. Game Develop. Conf.*, 2006, pp. 4.

[82] S. Álvarez Napagao *et al.*, "Conciens: Organizational awareness in real-time strategy games," 2012.

[83] S. Alvarez-Napagao *et al.*, "Socially-aware emergent narrative," *Agents for Educational Games and Simulations*, New York, NY, USA: Springer-Verlag, 2012, pp. 139–150.

[84] H. Yu *et al.*, "Exploring the application of computer game theory to automated assembly," *Procedia Comput. Sci.*, vol. 15, pp. 266–273, 2012.

[85] G. Rebolledo-Mendez, S. de Freitas, and A. R. G. Gaona, "A model of motivation based on empathy for AI-driven avatars in virtual worlds," in *Proc. Conf. Games Virtual Worlds Serious Appl.*, 2009, pp. 5–11.

[86] P. Jepp, M. Fradinho, and J. M. Pereira, "An agent framework for a modular serious game," in *Proc. 2nd Int. Conf. Games Virtual Worlds Serious Appl.*, 2010, pp. 19–26.

[87] C. Qu, W. Brinkman, P. Wiggers, and I. Heynderickx, "The effect of priming pictures and videos on a question–answer dialog scenario in a virtual environment," *Presence*, vol. 22, no. 2, pp. 91–109, 2013.

[88] R. Davis and J. J. King, "The origin of rule-based systems in AI," Rule-Based Expert Systems: The Mycin Experiments of the Stanford Heuristic Programming Project, 1984.

[89] G. A. E. Khayat, T. F. Mabrouk, and A. S. Elmaghraby, "Intelligent serious games system for children with learning disabilities," in *Proc. IEEE 17th Int. Conf. Comput. Games*, 2012, pp. 30–34.

[90] J. Haladjian, D. Ismailović, B. Köhler, and B. Brügge, "A quick prototyping framework for adaptive serious games with 2D physics on mobile touch devices," in *Proc. IADIS Int. Conf. Mobile Learn.*, 2012, pp. 197–204.

[91] A. Arya, S. DiPaola, and A. Parush, "Perceptually valid facial expressions for character-based applications," *Int. J. Comput. Games Technol.*, 2009.

[92] H. W. Patton, "Learning via gaming: An immersive environment for teaching kids handwriting," in *Proc. 37th Annu. Front. Educ. Conf.—Global Engineering: Knowledge Without Borders, Opportunities Without Passports*, 2008.

[93] A. Ward, M. McKeown, C. Utay, O. Medvedeva, and R. Crowley, "Interactive stories and motivation to read in the raft dyslexia fluency tutor," *Intelligent Virtual Agents*, New York, NY, USA: Springer-Verlag, 2012, pp. 260–267.

[94] L. M. Rojas-Barahona *et al.*, "Building and exploiting a corpus of dialog interactions between french speaking virtual and human agents," in *Proc. 8th Int. Conf. Lang. Resources Eval.*, 2012, pp. 1428–1435.

[95] A. J. Souza *et al.*, "An integrated development model for character-based games," in *Proc. IEEE VIII Brazilian Symp. Games Digit. Entertain.*, 2009, pp. 191–196.

[96] M. G. Core *et al.*, "Building explainable artificial intelligence systems," in *Proc. Nat. Conf. Artif. Intell.*, 2006, vol. 21, no. 2, pp. 1766.

[97] A. El Rhalibi, N. Baker, and M. Merabti, "Emotional agent model and architecture for NPCs group control and interaction to facilitate leadership roles in computer entertainment," in *Proc. ACM SIGCHI Int. Conf. Adv. Comput. Entertain. Technol.*, 2005, pp. 156–163.

[98] K. Sehaba and A. M. Hussaan, "Goals: Generator of adaptive learning scenarios," *Int. J. Learn. Technol.*, vol. 8, no. 3, pp. 224–245, 2013.

[99] D. Benedettelli, “Finite state machines,” *Creating Cool MINDSTORMS NXT Robots*, pp. 47–58, 2008.
[100] A. Szczesna, J. Grudzinski, T. Grudzinski, R. Mikuszewski, and A. Debowski, “The psychology serious game prototype for preschool children,” in *Proc. IEEE 1st Int. Conf. Serious Games Appl. Health*, 2011, pp. 1–4.
[101] C. T. Tan, A. Johnston, K. Ballard, S. Ferguson, and D. Perera-Schulz, “Speak-man: Towards popular gameplay for speech therapy,” in *Proc. 9th Australasian Conf. Interactive Entertain., Matters of Life and Death*, 2013, pp. 28.
[102] M. Rehm and K. Leichtenstern, “Gesture-based mobile training of intercultural behavior,” *Multimedia Syst.*, vol. 18, no. 1, pp. 33–51, 2012.
[103] D. L. Ines and G. Abdelkader, “Mixed reality serious games: The therapist perspective,” in *Proc. IEEE 1st Int. Conf. Serious Games Appl. Health*, 2011, pp. 1–10.
[104] H. Li, H. Munoz-Avila, L. Ke, C. Symborski, and R. Alonso, “Discovery of player strategies in a serious game,” in *Proc. 1st AAAI Conf. Human Comput. Crowdsourcing*, 2013.
[105] I. N. Sukajaya *et al.*, “Multi-parameter dynamic difficulty game’s scenario using Box-Muller of Gaussian distribution,” in *Proc. IEEE 7th Int. Conf. Comput. Sci. Educ.*, 2012, pp. 1666–1671.
[106] V. Wattanasoontorn, I. Boada, C. Blavi, and M. Sbert, “The framework of a life support simulation application,” *Procedia Comput. Sci.*, vol. 15, pp. 293–294, 2012.
[107] A. Yessad, J. Labat, and F. Kermorvant, “Segae: A serious game authoring environment,” in *Proc. IEEE 10th Int. Conf. Adv. Learn. Technol.*, 2010, pp. 538–540.
[108] J. R. Rankin and S. S. Vargas, “FPS extensions modelling ESGS,” in *Proc. 2nd Int. Conf. Adv. Comput.-Human Interactions*, 2009, pp. 152–155.
[109] A. Sagae, W. L. Johnson, and R. Row, “Serious game environments for language and culture education,” in *Proc. NAACL HLT Demonstration Session. Assoc. Comput. Linguistics*, 2010, pp. 29–32.
[110] B. Duggan, H. McAtamney, and F. Mtenzi, “Learning games programming with Dalek world,” in *Proc. 7th Int. Conf. Comput. Games, AI, Animation, Mobile, Educational and Serious Games, CNBDI*, 2005.
[111] B. Morgan, F. Kehtkar, A. Graesser, and D. Shaffer, “Automating the mentor in a serious game: A discourse analysis using finite state machines,” in *Proc. HCI Int. Posters Extended Abstracts*, 2013, pp. 591–595.
[112] D. Irvine and M. A. Gongora, “Cogbox-combined artificial intelligence methodologies to achieve a semi-realistic agent in serious games,” *Artificial Intelligence and Soft Computing*, New York, NY, USA: Springer-Verlag, 2010, pp. 492–499.
[113] G. Flórez-Puga, M. Gomez-Martin, B. Diaz-Agudo, and P. Gonzalez Calero, “Dynamic expansion of behaviour trees,” in *Proc. Artif. Intell. Interactive Digit. Entertain. Conf.*, pp. 36–41.
[114] V. Wendel *et al.*, “Woodment: Web-based collaborative multiplayer serious game,” *Trans. Edutainment IV*, pp. 68–78, 2010.
[115] P. McDowell, R. Darken, J. Sullivan, and E. Johnson, “Delta3d: A complete open source game and simulation engine for building military training systems,” *J. Defense Modeling Simul., Appl. Methodol. Technol.*, vol. 3, no. 3, pp. 143–154, 2006.
[116] B. G. Silverman *et al.*, “Nonkin village: An embeddable training game generator for learning cultural terrain and sustainable counter-insurgent operations,” *Agents for Games and Simulations*, New York, NY, USA: Springer-Verlag, 2009, pp. 135–154.
[117] A. Binsubaih, S. Maddock, and D. Romano, “A serious game for traffic accident investigators,” *Interactive Technol. Smart Educ.*, vol. 3, no. 4, pp. 329–346, 2006.
[118] V. Šisler, C. Brom, J. Cuhra, K. Činátl, and J. Gemrot, “Stories from the history of Czechoslovakia, a serious game for teaching history of the Czech lands in the 20th century—Notes on design concepts and design process,” in *Proc. Entertain. Comput.*, 2012, pp. 67–74.
[119] S. Bakkes, C. T. Tan, and Y. Pisan, “Personalised gaming: A motivation and overview of literature,” in *Proc. 8th Australasian Conf. Interactive Entertain., Playing the System*, 2012, pp. 4.
[120] L. Derbali, P. Chalfoun, and C. Frasson, “A theoretical and empirical approach in assessing motivational factors: From serious games to an its,” in *Proc. 24th Int. Florida Artif. Intell. Res. Soc. Conf.*.
[121] W. Husain, M. H. M. Adnan, L. K. Ping, J. Poh, and L. K. Meng, “Myhealthykids: Intelligent obesity intervention system for primary school children,” in *Proc. 3rd Int. Conf. Digit. Inf. Process. Commun.*, 2013, pp. 627–633.
[122] A. Weichselbraun, S. Gindl, and A. Scharl, “Using games with a purpose and bootstrapping to create domain-specific sentiment lexicons,” in *Proc. 20th ACM Int. Conf. Inf. Knowl. Manage.*, 2011, pp. 1053–1060.
[123] F. Keshtkar, C. Burkett, A. Graesser, and H. Li, “Detecting players personality behavior with any effort of concealment,” *Computational Linguistics and Intelligent Text Processing*, New York, NY, USA: Springer-Verlag, 2012, pp. 502–514.
[124] F. Vaassen and W. Daelemans, “Emotion classification in a serious game for training communication skills,” in *Proc. Comput. Linguist. Netherlands*, 2010.
[125] K. C. Tseng and C.-C. Wu, “An expert fitness diagnosis system based on elastic cloud computing,” *Sci. World J.*, 2014.
[126] J. Feldman, A. Monteserin, and A. Amandi, “Detecting students’ perception style by using games,” *Comput. Educ.*, vol. 71, pp. 14–22, 2014.
[127] S. N. W. Shamsuddin, H. Ugail, V. Lesk, and E. Walters, “Vread: A virtual simulation to investigate cognitive function in the elderly,” in *Proc. IEEE Int. Conf. Cyberworlds*, 2012, pp. 215–220.
[128] B. Morgan, F. Keshtkar, Y. Duan, P. Nash, and A. Graesser, “Using state transition networks to analyze multi-party conversations in a serious game,” *Intelligent Tutoring Systems*, New York, NY, USA: Springer-Verlag, 2012, pp. 162–167.
[129] J. Rowe *et al.*, “Crystal island: A narrative-centered learning environment for eighth grade microbiology,” in *Proc. Workshop Intell. Educ. Games/14th Int. Conf. Artif. Intell. Educ.*, Brighton, U.K., 2009, pp. 11–20.
[130] L. Zhang *et al.*, “Data fusion for difficulty adjustment in an adaptive virtual reality game system for autism intervention,” in *Proc. HCI Int. Posters Extended Abstracts*, 2014, pp. 648–652.
[131] M.-D. Otis and B. Menelas, “Toward an augmented shoe for preventing falls related to physical conditions of the soil,” in *Proc. IEEE Int. Conf. Syst. Man Cybern.*, 2012, pp. 3281–3285.
[132] D. Puzenat and I. Verlut, “Behavior analysis through games using artificial neural networks,” in *Proc. 3rd Int. Conf. Adv. Comput.-Human Interactions*, 2010, pp. 134–138.
[133] R. L. Lamb, L. Annetta, D. B. Vallett, and T. D. Sadler, “Cognitive diagnostic like approaches using neural-network analysis of serious educational videogames,” *Comput. Educ.*, vol. 70, pp. 92–104, 2014.
[134] M. A. Syufagi, M. H. Purnomo, and M. Hariadi, “Tendency of players is trial and error: Case study of cognitive classification in the cognitive skill games,” *Jurnal Ilmu Komputer dan Informasi*, vol. 5, no. 1, pp. 31, 2012.
[135] C. Mills and B. Dalgarno, “A conceptual model for game-based intelligent tutoring systems,” in *Proc. Australasian Soc. Comput. Learn. Tertiary Educ.*, 2007.
[136] C. Grappiolo, Y.-G. Cheong, J. Togelius, R. Khaled, and G. N. Yannakakis, “Towards player adaptivity in a serious game for conflict resolution,” in *Proc. 3rd Int. Conf. Games Virtual Worlds Serious Appl.*, 2011, pp. 192–198.
[137] H. Hildmann, A. Uhlemann, and D. Livingstone, “A mobile phone based virtual pet to teach social norms and behaviour to children,” in *Proc. 2nd IEEE Int. Conf. Digit. Games Intell. Toys Based Educ.*, 2008, pp. 15–17.
[138] R. Arrabales, A. Ledezma, and A. Sanchis, “Towards conscious-like behavior in computer game characters,” in *Proc. IEEE Symp. Comput. Intell. Games*, 2009, pp. 217–224.
[139] O. Miglino, O. Gigliotta, M. Schembri, and A. Di, “Collective adaptive agents as techniques to build-up edutainments systems,” in *Proc. Italian Workshop Artif. Life Evol. Comput.*, 2012.
[140] O. Gigliotta, O. Miglino, M. Schembri, and A. Di, “Building up serious games with an artificial life approach: Two cases studies,” *Evolution, Complexity and Artificial Life*, S. Cagnoni, M. Mirolli, M. Villani, Eds. New York, NY, USA: Springer-Verlag, 2013.
[141] M. Syufagi, P. Hery, and M. Hariadi, “Modeling serious games based on cognitive skill classification using learning vector quantization with petri net,” in *Proc. IEEE Int. Conf. Adv. Comput. Sci. Inf. Syst.*, 2011, pp. 159–164.
[142] M. A. Syufagi, M. Hariadi, and M. H. Purnomo, “Petri net model for serious games based on motivation behavior classification,” *Int. J. Comput. Games Technol.*, pp. 1, 2013.
[143] A. Ram, S. Ontañón, and M. Mehta, “Artificial intelligence for adaptive computer games,” in *Proc. FLAIRS Conf.*, 2007, pp. 22–29.
[144] A. Tobail, J. Crowe, and A. Arisha, “Learning by gaming: Supply chain application,” in *Proc. Winter Simul. Conf.*, 2011, pp. 3935–3946.
[145] A. McKenzie and G. McCalla, “Serious games for professional ethics: An architecture to support personalization,” in *Proc. 14th Int. Conf. Artif. Intell. Educ. Workshops*, 2009, pp. 69.
[146] S. Triki, N. B. B. Saoud, J. Dugdale, and C. Hanachi, “Coupling case based reasoning and process mining for a web based crisis management decision support system,” in *Proc. IEEE 22nd Int. Workshop Enabling Technol., Infrastructure for Collaborative Enterprises*, 2013, pp. 245–252.

[147] I. Hulpuş, C. Hayes, and M. O. Fradinho, "A framework for personalised learning-plan recommendations in game-based learning," *Recommender Systems for Technology Enhanced Learning*, New York, NY, USA: Springer-Verlag, 2014, pp. 99–122.
[148] M. Floryan and B. Woolf, "Rashi game: Towards an effective educational 3D gaming experience," in *Proc. 11th IEEE Int. Conf. Adv. Learn. Technol.*, 2011, pp. 436–437.
[149] C. Forsyth *et al.*, "Didactic galactic: Types of knowledge learned in a serious game," *Artificial Intelligence in Education*, New York, NY, USA: Springer-Verlag, 2013, pp. 832–835.
[150] C.-R. Song, "Design and usability of web-based serious game for Taiwanese EFL undergraduate students," in *Proc. Int. Conf. Netw./Int. Conf. Syst./Int. Conf. Mobile Commun. Learn. Technol.*, 2006, pp. 220–220.
[151] A. Tobail, J. Crowe, and A. Arisha, "Serious gaming learning: Supply chain multi-agent web-based simulation game," 2012.
[152] R. Lopes and R. Bidarra, "A semantic generation framework for enabling adaptive game worlds," in *Proc. 8th Int. Conf. Adv. Comput. Entertain. Technol.*, 2011, pp. 6.
[153] I. Hulpuş, M. Fradinho, and C. Hayes, "On-the-fly adaptive planning for game-based learning," *Case-Based Reasoning. Research and Development*, New York, NY, USA: Springer-Verlag, 2010, pp. 375–389.
[154] J.-S. Ahn and W.-H. Lee, "Using EEG pattern analysis for implementation of game interface," in *Proc. IEEE 15th Int. Symp. Consumer Electron.*, 2011, pp. 348–351.
[155] T. D. Parsons and J. L. Reinebold, "Adaptive virtual environments for neuropsychological assessment in serious games," *IEEE Trans. Consumer Electron.*, vol. 58, no. 2, pp. 197–204, 2012.
[156] R. Berta, F. Bellotti, A. De Gloria, D. Pranantha, and C. Schatten, "Electroencephalogram and physiological signal analysis for assessing flow in games," *IEEE Trans. Comput. Intell. AI Games*, vol. 5, no. 2, pp. 164–175, 2013.
[157] S. Bernardini, K. Porayska-Pomsta, and H. Sampath, "Designing an intelligent virtual agent for social communication in autism," in *Proc. 9th Annu. AAAI Conf. Artif. Intell. Interactive Digit. Entertain.*, 2013.
[158] S. Bernardini, K. Porayska-Pomsta, and T. J. Smith, "Echoes: An intelligent serious game for fostering social communication in children with autism," *Inf. Sci.*, 2013.
[159] E. M. Raybourn, N. Fabian, E. Tucker, and M. Willis, "Beyond game effectiveness Part II: A qualitative study of multi-role experiential learning," in *Proc. Interservice/Industry Training Simul. Educ. Conf.*, 2010, no. 1.
[160] M. Zhang *et al.*, "The framework and implementation of virtual network marathon," in *Proc. IEEE Int. Symp. VR Innovation*, 2011, pp. 161–167.
[161] J. R. Quinlan, "Decision trees and decision-making," *IEEE Trans. Syst. Man Cybern.*, vol. 20, no. 2, pp. 339–346, 1990.
[162] G. Mountrakis, J. Im, and C. Ogole, "Support vector machines in remote sensing: A review," *ISPRS J. Photogrammetry Remote Sens.*, vol. 66, no. 3, pp. 247–259, 2011.
[163] J. Solana *et al.*, "Intelligent therapy assistant (ITA) for cognitive rehabilitation in patients with acquired brain injury," *BMC Med. Inf. Decision Making*, vol. 14, no. 1, pp. 58, 2014.
[164] J. Alvarez, D. Djaouti, and O. Rampnoux, *Serious Games Market: Some Key Figures (From 1950's to 2000's)*, Paris, France: IDATE, 2009.
[165] T. M. Connolly, E. A. Boyle, E. MacArthur, T. Hainey, and J. M. Boyle, "A systematic literature review of empirical evidence on computer games and serious games," *Comput. Educ.*, vol. 59, no. 2, pp. 661–686, 2012.
[166] T. S. Portal, "Number of smartphones sold to end users worldwide from 2007 to 2014 (in million units)," Online. [Available]: http://statista.com/statistics/263437/global-smartphone-sales-to-end-users-since-2007/
[167] I. Mayer *et al.*, "The research and evaluation of serious games: Toward a comprehensive methodology," *Brit. J. Educ. Technol.*, vol. 45, no. 3, pp. 502–527, 2014.
[168] G. Sim, S. MacFarlane, and J. Read, "All work and no play: Measuring fun, usability, and learning in software for children," *Comput. Educ.*, vol. 46, no. 3, pp. 235–248, 2006.
[169] M. Ernst, "Choosing a venue: Conference or journal?," 2008.
[170] M. Muir and C. Conati, "An analysis of attention to student—Adaptive hints in an educational game," *Intell. Tut. Syst.*, pp. 112–122, 2012.

Maite Frutos-Pascual graduated in telecommunications engineering from the University of Deusto, Bilbao, Spain, in 2011. She received the M.Sc. degree in development and integration of software solutions from the University of Deusto in 2012. She is currently working toward the Ph.D. degree in the area of biofeedback and serious games for health.

She has published several scientific articles in both indexed journals by ISI Web of Science and in several international conferences.

Begoñya García-Zapirain graduated in telecommunications engineering and specialized in telematics at the University of the Basque Country (UPV/EHU), Leioa, Spain. She received the Ph.D. degree (*summa cum laude*) in the pathological speech digital processing field in 2003. She received an Executive MBA from the University of the Basque Country, in 2011, with the best student award, and in 2012, she graduated from the Advanced Program in Health Management at Deusto Business School, Deusto University, Bilboa, Spain.

After five years working for ZIV Company, in 1997, she joined the Engineering Faculty at the University of Deusto, as a Lecturer in Signal Theory and Electronics, where she led the Telecommunications Department from 2002 to 2008.

Dr. García-Zapirain received the Accésit to the Ada Byron Award to the Technologist Woman 2015. In recognition of the quality of its research activities, the research group she leads won the Research Award 2007 UDGrupo Santander, the ONCE Euskadi Solidarity Award 2007, the award for the best article in the Games 2009 International Congress, the prize for the best poster at ISIVC 2008, and was the finalist for the "Social Innovation in Ageing—The European Award 2014."