INVITED PAPER

Affective Game Computing: A Survey

This article surveys affective computing applications in gaming. Alongside the state-of-play, principles, approaches, and tools, it discusses the affective loop: game affect elicitation, sensing, detection, and adaptation.

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ABSTRACT | This article surveys the current state-of-the-art in affective computing (AC) principles, methods, and tools as applied to games. We review this emerging field, namely affective game computing, through the lens of the four core phases of the affective loop: game affect elicitation, game affect sensing, game affect detection, and game affect adaptation. In addition, we provide a taxonomy of terms, methods, and approaches used across the four phases of the affective game loop and situate the field within this taxonomy. We continue with a comprehensive review of available affect data collection methods with regard to gaming interfaces, sensors, annotation protocols, and available corpora. This article concludes with a discussion on the current limitations of affective game computing and our vision for the most promising future research directions in the field.

KEYWORDS | Affective computing (AC); affective loop; games; player modeling; survey; taxonomy.

I. INTRODUCTION

Over a third of the Earth's population is playing games by now—with the projected number of gamers rising up to 3.3 billion by 2024 [1]. We could argue that game playing at this massive scale is probably the largest ongoing experiment of human behavior and experience. The emotional patterns that a player goes through are deeply interwoven in the design of any game. This central role of affect interaction in this domain makes games an ideal test bed for the study of affective computing (AC) [2]. Games, however, are not merely an important domain for AC. As a matter of fact, games have shaped and advanced the AC field in numerous ways given the unique challenges they pose and opportunities they bring to affective interaction.

Looking at digital games through the lens of the affective loop [3], one can only observe benefits for AC research and innovation. When it comes to emotion elicitation, games define one of the richest forms of human–computer interaction and thus offer highly multimodal and dynamic ways to elicit affect. Moving on to affect sensing, the availability of game engine and sensor technology brings AC researchers unprecedented opportunities for measuring manifestations of affect way beyond physiology and verbal and nonverbal communication (e.g., game analytics and in-game social activity). Affect detection benefits from the massive gameplay corpora available in the wild, e.g., over streaming services [4]. Finally, affect adaptation in games can be achieved via highly diverse stimuli that vary from AI-controlled expressive agents to content generators of various types [5], [6].

In this article, we survey the emerging research area at the intersection of AC and games, namely affective game computing. In particular, we build on the affective loop paradigm [3], [7] (see Section II) and survey core contributions in the areas of affect elicitation, sensing, detection, and adaptation in games (see Sections III–VI). We use indicative examples from both the game industry and academic research showcasing the advancements of AC through games but also the benefits AC offers to games and their development. Throughout our survey, we identify core terms, methods, and approaches that we, later on, use to situate the affective game computing field as a whole (see Section VII). Moreover, our survey puts an emphasis on state-of-the-art data collection methods in games relating to interfaces, sensing devices, and annotation protocols (see Section VIII) and the available affect corpora (see Section IX). This article concludes with a detailed list of current limitations of the available methods and technologies (see Section X) and outlines a number of promising future research directions for affective game

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computing (see Section XI). We feel (and hope) that all aforementioned studies, methods, resources, and tools contained in this survey article will serve as a guide for affective game computing researchers and will also lower the entry bar for any newcomer to this emerging research and innovation field.

A. Contributions of This Article

The field of AC in the domain of games has been studied extensively over the last 15 years. The literature is rich in this application area—as one can observe through the volume of references in this article. Despite the variety and breadth of the studies covered, however, only a few papers have reviewed this research field in a comprehensive and detailed manner to the degree this article does. Indicatively, an early short survey of the field focused on the relationship between emotion and games [8] and introduced the concept of the affective loop in games. The edited volume *Emotion in Games* [9] provides broad coverage of several aspects of AC research in games, but it does not survey the field comprehensively and in a systematic fashion. Yannakakis and Togelius [10] offered an entire chapter on player modeling—the use of computational means to capture aspects of playing behavior and experience—which touches upon some of the aspects covered here. Two more recent relevant surveys include the work of Robinson et al. [11] who examined the use of physiological sensors in the field of human–computer interaction and Navarro et al. [12] who surveyed biofeedback interaction specifically in videogames for general entertainment.

In contrast to all the aforementioned attempts, this article introduces the affective game computing field and surveys it in a holistic, systematic, and comprehensive manner. In particular, this article covers both industry and academic examples, and it offers a taxonomy of terms and methods through which we can map the critical studies in the field. Furthermore, this article surveys existing corpora, methods, and annotation protocols, provides guidelines for the newcomer in this field, and discusses the next most promising research steps forward.

II. AFFECTIVE GAME LOOP

The affective loop first introduced by Höök [3] and Sundström [7] has become a dominant AC paradigm that is able to represent any affective interaction in a general fashion. The affective loop comprises four core sequential phases that enable an affective interaction: affect elicitation, affect sensing, affect detection, and affect adaptation. When the affective loop principle is applied to games, the resulting paradigm has been defined as the affective game loop [8] (see Fig. 1). Before delving into the details of the AC and games survey, in this section, we outline the key elements of each phase of the affective game loop as follows.

1) *Elicitation:* In this initial phase of the loop, the game yields affective responses to players via a multitude of available affect elicitors such as game agents and game content. We detail those elicitors and survey the corresponding literature on game affect elicitation in Section III.
2) *Sensing:* Once affect is elicited, players manifest it in numerous ways. The second phase of the affective game loop is responsible for sensing those manifestations via sensor and tracking technology as detailed in Section IV.
3) *Detection:* Given appropriate signals obtained from the sensed multimodal player input and human demonstrations of affect (such as player experience annotations), one can build mathematical formulations (e.g., via statistical machine learning) that are capable of inferring the annotated affect accurately based on the user signals. Details on game affect detection methods are provided in Section V.
4) *Adaptation:* In the last phase of the affective game loop, the game is required to offer the next sequence of in-game stimuli so that the experience of the player is set within predetermined bounds. We survey methods and studies on game affect adaptation in Section VI.

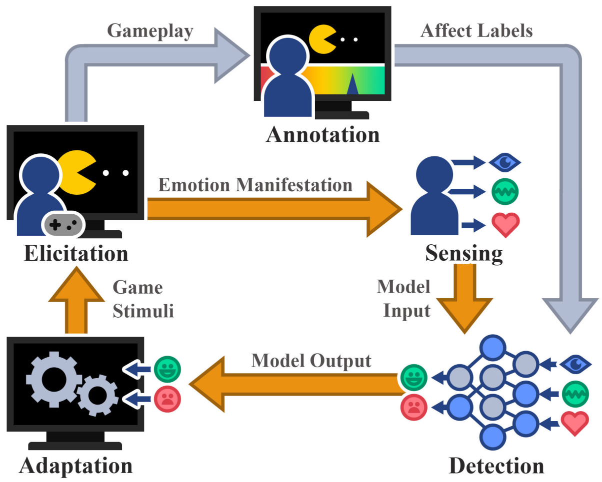

Fig. 1. ***High-level illustration of the affective game loop. The orange arrows depict the core steps of the loop via elicitation, sensing, adaptation, and detection. The gray arrows show how affect annotation can be integrated into the loop.***

III. GAME AFFECT ELICITATION

As mentioned earlier, games are equipped with a rather diverse set of stimuli that are capable of eliciting a wide spectrum of emotions in players. In this section, we provide a taxonomy of such stimuli independently of the affective states they might be able to elicit.

Importantly, the context of the game environment, the game genre, the form of interfacing, the number of players, potential social aspects of the game, and the overall objective of the game are foundational and they impact any other in-game elicitor covered here. For our taxonomy of elicitors, we largely adopt and build upon the taxonomies

Table 1 Taxonomy of Game Affect Elicitors

Category	Subcategory	Elicitors
Context	Genre	Shooter, platformer, racing, strategy, adventure, etc.
	Platform	Mobile, Augmented Reality (AR), VR, console, desktop.
	Number of players	single, one-and-a-half, two-player, multi-player
	Observability	Fully observable vs. partially observable game
	Stochasticity	Deterministic vs. non-deterministic game
	Time granularity	Real-time vs. continuous
	Action Space	Player actions available: 2 to many
AI Agent		Navigation, expression, exploration, verbal/non-verbal interaction
Content		Visuals, Audio, Narrative, Game Design, Levels, Gameplay [5]

introduced by Yannakakis and Togelius [10]. In particular, as summarized in Table 1, we identify three categories of affect elicitors in games, namely game context, game agent, and game content. We discuss these categories in detail next followed by an indicative example of affect elicitation in games in Section III-A.

Game context refers to the game's genre, the platform used, and the game's characteristics that collectively define the momentaneous state of the game. A player can obviously affect the dynamic aspects of the game context (i.e., the game state) and vice versa, and the game context can affect the gameplay and elicit affect patterns. The importance of game context is critical for player affect modeling as the context of the game needs to be considered for reliable affect detection. in other words, any player's reactions cannot be dissociated from the stimulus that elicited them. Following the taxonomy introduced in [10], the core game characteristics that fall under the game context group include the number of players, the observability of play, the stochasticity of the game, the time granularity, and the action space for the player (see Fig. 2). Under the game agent category, we fit any affect elicitor related to AI-controlled agents that might be available in the game. Examples include agent facial expression, verbal, and nonverbal agent behavior, social agent behavior, and individual agent behavioral patterns that can affect a player's experience. Finally, game content refers to any content type existent in a game that is not related to AI agent behaviors as those are covered in the game agent category (i.e., the virtual environment [13]). Building on the categorization of Liapis et al. [5], each game is viewed as a synthesis of creative facets available, which include the design of the games (i.e., rules and mechanics), the game level, and the creative ways a human plays the game (i.e., gameplay). Depending on the game available, content types may include visuals, audio, narrative, and even novel control modalities [14].

All the abovementioned elicitors can affect the experience of play and are met in various configurations in games. It is rarely the case—as in most other domains of AC—that only one elicitor type (e.g., an image, or a sound) is active at a time. In games, instead, affect elicitors are orchestrated [6], [15] in groups, thereby offering rich and multifaceted affective interactions [14], [15], [16], [17], [18], [19]. As an example of such an orchestration process, think of a scary story that is told by an expressive agent who is placed in a dungeon level with the corresponding visual and audio effects, and the appropriate virtual camera placement and lighting.

It is important to note that the game context is static meaning that no aspect of it can be altered by the player or the game. As a result, the game context cannot act as a dynamic affect stimulus when the affective loop reaches its adaptation phase. One could think of games that change their genre, their mode of interaction (e.g., from virtual reality (VR) to desktop) [20] and the number of players, but those alterations are rare. Therefore, in this section, instead of surveying the existing literature with respect to all possible affect elicitors in games, we will survey only the game context category. We will then survey AI agents and content in Section VI as these two categories include dynamic stimuli that can be altered during the game affective interaction.

Aspects of the game context have been predominantly included as a modality of input for affect detection in games (e.g., [21], [22], [23], [24], [25], [26], [27], [28], [29], and [30], among others). In most of these studies (e.g., [24], [23], and [30]), the game context does not

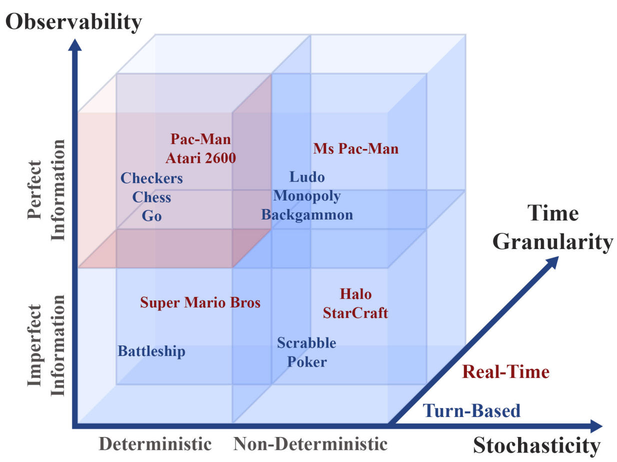

Fig. 2. *Characteristics of games: examples across the dimensions of stochasticity, observability, and time granularity. While classical algorithms, such as minimax, are only able to solve games in the red square, AI methods that can approximate a decision tree (e.g., Monte Carlo tree search) can solve games in the blue squares as well. Adopted from [10] with authors' permission.*

refer to any of the aspects included in Table 1 but rather to aspects of the game environment such as level features. We could argue that the game context aspects covered in Table 1 become highly relevant for affect detection once one performs studies on general affect modeling [31], [32], [33], [34]. Very few studies have explored modalities of user input in isolation of the game context. For example, Makantasis et al. [35] built models of affect based solely on physiology for the purpose of comparison against models that fused aspects of in-game video and audio.

A. Indicative Examples

In this section, we will provide an indicative example of affect elicitors that have been used in a game that realizes the game affection loop. In particular, we will outline the StartleMart post-traumatic stress disorder (PTSD) game (see Fig. 3), which was designed and developed as a form of virtual exposure therapy [36], [37]. The game adapts to the level of stress of PTSD patients—as measured via their skin conductance—by triggering certain auditory and visual stimuli including war sounds, stressful social settings, and war flashback moments. When it comes to the context of the game, StartleMart can be characterized as a training game with a health purpose (i.e., PTSD treatment) (genre) that takes place in a supermarket, played in desktop (platform) by a single player (number of players). The game is partially observable (observability) as it features a first-person view over a 3-D level, it is deterministic (stochasticity) and continuous (time granularity), and the player actions are limited to moving around in a continuous environment and picking objects (action space). The game context as described above acts as a mild stressor for patients suffering from PTSD. A preselected number of in-game stimuli—provided in the form of audio, visuals, and video cut-scenes—act as personalized intense stress elicitors. More details about StartleMart can be found in [36], [37], and [38].

Fig. 3. ***Screenshots of StartleMart [36]; a biofeedback game designed as a virtual stress inoculation and exposure therapy tool.***

IV. GAME AFFECT SENSING

Moving on to phase 2 of the affective game loop in this section, we will first survey the multiple ways we can sense how a player feels based on their manifested emotions (see Section IV-A) and will then survey the available methods we can obtain affect annotations and labels in games (see Section IV-B). From an affect modeling perspective, we will first focus on the input of the model and then cover its output. Similar to Section III, we start by introducing our taxonomy, then survey the corresponding literature, and end with an indicative example that is presented in more detail.

A. Sensing the Input

Player emotional manifestations may be sensed through variations of gameplay patterns, alterations in a player's attention, level of focus, and changes in the player's physiology, facial expression, posture, and speech. Monitoring such alterations may assist in recognizing and constructing the player's model.

Any affect model of players relies on data of the manifested affective experience. Such data define the input of the affect model and can be obtained directly through the game engine or with the help of additional sensors. These sensors are either available through the various platforms (e.g., eye tracking featured in a VR headset) or they are integrated into the game (e.g., a skin conductance sensor that interfaces with the game)—for a recent survey of physiological sensors in affective game research, see also [11]. Following the player modeling taxonomies of [8] and [10], we argue that sensing affect manifestations in games can be of the two main categories: gameplay and objective sensing. The two categories are detailed in the remainder of this section and summarized in Table 2.

1) Gameplay: As games affect the player's cognitive processing patterns and cognitive focus, our core assumption is that players' in-game behavior is linked directly to their experience. As a result, players' affect can be derived through the analysis of their in-game interaction patterns considering game context variables [39], [40]. Gameplay refers to anything a player does in a game environment, which is collected via in-game logs of any type such as user interface selections, preferences, or in-game actions. In particular, gameplay includes any aspect that

Table 2 Taxonomy of Game Affect Sensing

I/O	Category	Subcategory	Sensing Options
Input	Gameplay		Ad-hoc gameplay features, pixels, audio, preferences, in-game actions
	Objective	Physiology	EDA, ECG, EEG, EMG
		Camera-based	Facial Expression, Head Pose, Gestures, Body movement
		Verbal	Speech
Output	Subjective		Human demonstrations of experience, annotations, questionnaires

can be derived from the interaction between the player and the game directly. Such aspects—also broadly known as player metrics [41], [42]—include detailed attributes of the player's behavior, which are based on interactions with game elements such as objects, nonplayer characters, and levels. Popular examples of attributes that are directly linked with gameplay include spatial locations of players and key events viewed as heat maps [43] trajectories or aggregated descriptive data [32], communication with other players or an audience [4], and all the way to pixel colors of the game's footage [33], [34].

A key limitation of gameplay is that the player affect is only observed indirectly. For example, a player that shows limited interaction through their logged gameplay data could be either planning their next quest, talking to their friend over the phone, or even feeling bored with the game. It is also important to note that affect models that are derived from gameplay data do not necessarily generalize across all players and games. Therefore, it is crucial that affect models are fine-tuned to the needs of players and manifest gameplay experiences of player personas [44] and ultimately individual players. One might even argue that gameplay data are not even relevant for particular games or players as the ad hoc design of the gameplay attributes might not be useful for capturing certain aspects of player affect.

2) Objective: This category refers to any signals available as a response to in-game stimuli. In particular, objective ways of sensing affect include physiological signals—electrodermal activity (EDA), electrocardiogram (ECG), electromyogram (EMG), and electroencephalogram (EEG) [45], [46], [47]—camera-based signals, including facial expression, head pose, gestures, and body movement [48], [49]; and verbal signals, including speech and body movements.

The analysis of physiological manifestations of psychology (i.e., psychophysiology) is well studied by now; see [11], [28], [50], [51], and [52], among many others. It is widely evidenced that arousing or tense events cause dynamic changes in both sympathetic (increase) and parasympathetic (decrease) nervous systems, whereas low arousal (e.g., relaxing or resting) states increase the activity on the parasympathetic nervous system. Such activity may cause observable alterations, for instance, in a player's facial expression, head pose, and EDA [53], [54]. A significant body of literature has focused on the relationship between a player's physiology in response to their gameplay patterns [21], [55], [56], [57], [58], [59], [60], [61], relying on ECG [62], photoplethysmography [60], [62], [63], EDA [36], [37], [38], [57], respiration [60], EEG [45], [64], [65], [66], and eye movement [67], [68]. In addition to physiology, the player's bodily expressions can reveal real-time affective responses from the gameplay stimuli. Such input modalities have been explored extensively in games and include facial expressions [69], [70], [71], [72], [73], muscle activation [22], [74], body movement and posture [67], [69], [75], [76], [77], haptics [78], and gestures [79], On a higher level, objective input can be viewed largely as either verbal or nonverbal. Verbal input includes speech-based modalities [80], [81], [82], [83], [84], while no-verbal input may rely on text [85], [86], [87] or any of the abovementioned modalities.

The limitations of objective inputs are several. First, most of the sensors are not available in a player's natural habitat (i.e., in the wild). Second, most sensors are intrusive, thereby affecting gameplay at large. Third, the signals obtained are usually noisy due to environmental conditions and hardware limitations. We discuss these limitations in more detail in Section X.

B. Sensing the Output

The output of any affect model is usually a set of particular states (e.g., happy), a scalar (e.g., the emotional dimensions of arousal and valence), or an ordinal relationship (e.g., tension is higher now than before). Sensing the output is predominately achieved through a subjective annotation process by the player themselves (first person) or by others (third person) such as game experience designers, peers, or external observers. Those annotated labels ideally need to be as close to the ground truth of playing experience as possible [10]. Sensing the most reliable affect labels for players is a tedious and laborious task, which defines a challenge in its own right. The area of affect annotation is long studied in the literature, yet there are still many open research questions left for the design of the ideal annotation collection protocol: first, who provides the labels (first or third person); second, is player experience represented as states or instead as intensity/magnitude; third, should annotations be provided in discrete time periods or continuously; and fourth, should the annotators be asked to give a magnitude label (e.g., frustration is 0.8) or an ordinal relationship (e.g., frustration is higher in this level segment). Some of these questions are addressed in the remainder of this article, particularly Sections V and VIII.

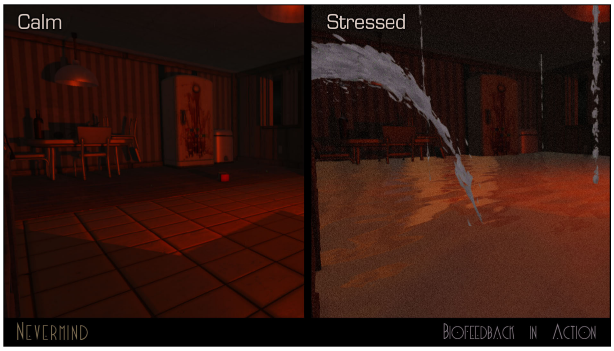

Fig. 4. ***Screenshot of Nevermind (Flying Mollusk, 2015) showcasing the elements of the game that can alter to elicit stress to the player. Image obtained from Erin Reynolds with permission.***

Fig. 5. ***Screenshot of Apex of Fear (2022). The dashboard showcases the player view and the multiple modalities available for sensing the players. Computational models of affect can be used to adapt the levels of fear according to a predetermined experience curve.***

C. Indicative Examples

At the moment of writing, there are a number of examples of commercial games that utilize physiological input from players. One particularly interesting example is Nevermind (Flying Mollusk, 2015), a biofeedback-based adventure horror game that adapts to the player's stress levels by altering the game's content, including visuals and sounds (see Fig. 4) [88]. A number of sensors, which monitor the player's heart rate variability, skin conductance, facial expressions, and gestures, are available for affective interaction with the game.

Our second affect sensing example comes from a collaborative project between academic and industrial partners named Apex of Fear (2022).[1] Apex of Fear is a VR horror game experience that adapts to its players' fear levels in real time based on their psychophysiological measures. The multimodal sensing capacities of Apex of Fear include EDA, respiration, electrocardiography, electromyography, eye tracking, and in-game events (see Fig. 5). The game is currently in its beta testing phase through which user data are collected for constructing reliable models of in-game fear based on the physiological manifestations of players.

Both of these examples focus on sensing the input rather than the output. While surveys and continuous annotation tools to measure player experience are used extensively in games research [89] and game industry user research [90], they rarely show up in commercial games. A possible explanation of why this happens is that most commercial games are presented as black boxes to the players. Game designers value immersive experiences highly [91], and therefore, pointed surveys that measure the output of emotions directly can uncover the inner workings of game systems, revealing the smoke-and-mirror nature of games. Recent advancements, however, within large-scale language models (LLMs) point toward a promising direction incorporating human affect labels for shaping and defining large-scale affect models in games. As shown by Lambert et al. [92], reinforcement learning (RL) from human feedback can greatly enhance the performance and personalize the output of large foundation models such as GPT-3 [93] and GPT-4 [94]. Human feedback may take the form of like/dislike labels or preferences among options (i.e., generated texts and/or images).

Even though general like/dislike labels already encode a form of affective feedback, detailed survey methods used in the games industry could inform future affect models in games. A good example of such a survey is the Ubisoft Player Experience Questionnaire (UPEQ) [95] designed to assess the motivational drives of players. The UPEQ questionnaire has been used successfully to model player's motivation based on simple behavioral patterns of players in the role-playing third-person shooter game Tom Clancy's The Division (Ubisoft, 2016) [96] (see Fig. 6).

V. GAME AFFECT DETECTION

In the third phase of the game affective loop, a computational model is requested to detect player affect based on the player modalities available. Because this affect model is trained to predict labels, the task of affect detection is largely viewed as a supervised learning paradigm [51] through which measurable attributes of the player

Fig. 6. ***Game footage from Tom Clancy's the division (Ubisoft, 2016).***

[1] https://apexoffear.com/

Table 3 Taxonomy of Game Affect Detection Methods

Category	**Subcategories**	**Learning Target**
Supervised Learning	Regression Classification Preference Learning	Numerical values Nominal categories Ordinal relations
Reinforcement Learning	Offline vs Online, Inverse Reinforcement Learning	Simulation of a human-like affective process

(model's input) are mapped to the player's affect state (model's output). Any supervised learning method can be used for inferring such a mapping, including decision trees and random forests, support vector machines, and shallow or deep neural network architectures. The data type of the affect label available determines the output type of the model and, in turn, the machine learning approach that is applicable. Numerical data can be modeled using regression methods, whereas nominal variables, such as emotion categories or arbitrary bins of numerical data (e.g., high versus low values based on a split criterion), are modeled via classification methods. Finally, ordinal observations (e.g., pairwise preferences or forced choices) can be trained via preference learning methods. It is also possible to create ordinal observations from numerical values (e.g., change in score) or even from nominal values in some cases (e.g., arousal intensity of labeled emotions) [97]. We detail the three supervised learning types in the following (see Table 3).

When the affect labels that need to be predicted are interval, affect modeling can be achieved via regression algorithms, including linear or polynomial regression, artificial neural networks, and support vector machines. Modeling player affect via regression has certain limitations and will most likely yield unreliable models as regression assumes that the target value to be predicted follows a numerical scale. A number of comprehensive studies [97], [98], [99], [100], [101], [102], [103] provide sufficient evidence against the use of regression for player experience modeling. Values obtained via magnitude-based annotation (e.g., ratings) should instead be converted to ordinal values via the second-order process described in [97].

If instead of numerical values player affect is represented as a set of classes (e.g., high versus low engagement), any classification method is applicable for learning to predict affect. Classes can represent both aspects of player experience—e.g., excited or frustrated player—and aspects of playing behavior such as quest completion times (e.g., low versus high completion time). Classification is ideal for modeling player experience if discrete annotations of experience are available as target outputs [104], [105], [106], [107]. Converting numerical values to classes (e.g., convert arousal annotations between 0 and 1 to low versus high arousal) might introduce data biases, which, in turn, might prove to be detrimental to modeling player affect [97], [98], [108].

Alternatively to regression and classification, preference learning [97], [109] methods can learn to predict affect from ordinal data such as affect ranks or preferences. The target values in the preference learning paradigm provide information for the relative relation between instances of the label we attempt to learn. For instance, labels are obtained by comparing two game levels in terms of engagement [25] or they can be retrieved via ordinal processing of an arousal trace [89], [110]. Largely speaking, the data analysis of ordinal labels follows the first-order process described in [97]. A large palette of algorithms is available for the task of preference learning, including linear statistical models and nonlinear approaches such as Gaussian processes [111], deep and shallow artificial neural networks [112], [113], [114], [115], neuro-evolutionary methods [116], and support vector machines [117]. Many of those methods are available in online accessible tools [118].

Grounded in extensive studies available in the literature [97], [98] and supported by contemporary research [115], [116], the selection of a supervised learning approach for modeling player affect becomes obvious. We argue that preference learning is a superior supervised learning method for player affect modeling; classification provides a good balance between simplicity and approximation of the ground truth of player experience, whereas regression is based on numerical affect annotations, which, in turn, yield models of questionable validity and reliability.

A. Affect Detection as RL

The affect detection task is traditionally viewed through the lens of supervised learning. However, alternative approaches have emerged beyond this paradigm recently. In particular, methods from RL have shown great potential for modeling player affect (see Table 3). The key motivation for the use of RL for modeling player affect is that it can capture the relative valuation of affective states as encoded internally by humans during play [119]. According to the RL perspective for modeling players, the derived RL policy can capture internal player states with no corresponding absolute target values such as decision-making, learnability, cognitive skills, or style [120]. The player model that is built via an RL process is expected to offer a psychometrically valid, abstract simulation of a human player's internal cognitive and/or affective processes. An agent equipped with such a model can be used to interpret human play or featured in AI agents, which can be used as playtesting bots or as believable human-like opponents [121], [122], [123].

These nontraditional ways of detecting players' affect are still in their infancy with only a few studies existent in racing and Atari-like 2-D games [121], [122], [124],

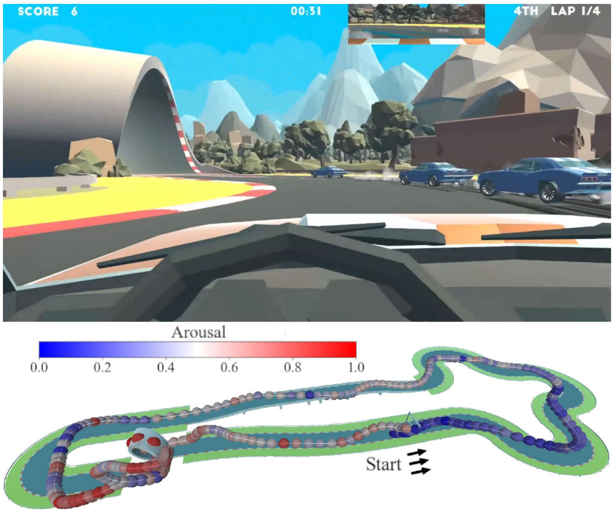

Fig. 7. ***Screenshot of the solid rally racing game [126] (top) and the generated behavioral and arousal traces of an RL agent that learns how to play like and "feel" like a human expert player (bottom) [122], [126].***

racing games [123], serious games [125], and first-person shooters [119].

B. Indicative Examples

We use racing games as the genre of the indicative examples we discuss in more detail here. Focusing on the game industry, the Drivatar imitation learning system of the Forza Motorsport series (2005–2022, Microsoft Game Studios) is the long-standing AI within a game title. Building on a set of simple rules and behavioral cloning techniques back in 2005, Drivatar has evolved to feature deep neural network approaches (in 2022) that imitate the way any player drives a car and simulate the player's driving style.[2] Even though modeling in Drivatar relies on behavioral human demonstrations, it is indicative of what player affect modeling can achieve in commercial-standard games if human affect demonstrations can be provided.

Moving from the game industry to a recent research example in the area of affect modeling, the work of Barthet et al. [122], [123], [126] is worth outlining. The authors in that series of papers import the highly successful RL algorithm Go-Explore [127] to the field of affect modeling in their attempt to model both behavioral and affective patterns of play. The resulting algorithm, namely Go-Blend, is able to blend human demonstrations of behavior and affect in a common representation, thereby allowing for believable playtesting. The generative Go-Blend agents are able to play and "feel" like human players of racing games by imitating their play and arousal traces (see Fig. 7).

[2] A video detailing the evolution of Drivatar is available here: https://www.youtube.com/watch?v=JeYP9eyIl4E.

VI. GAME AFFECT ADAPTATION

Computer games—as opposed to traditional media content such as images and videos—are interactive media that continuously react to the users' input. This interactivity can naturally accommodate mechanisms for real-time adaptation of game content aimed at adjusting player experience and realizing affective interaction [128]. One of the main reasons we can achieve meaningful affect-driven adaptation in games is because players are prepared for personalized experiences more than in any other form of human–computer interaction [8]. The relationship of players to adaptation mechanisms in games is highly dependent on their playing style, mood, experience, personality, and the efficiency of the adaptation with regard to player needs.

The last phase of the game affective loop involves the adaptation of in-game elements for eliciting particular affective patterns. We refer to such elements as actionable as they are linked and can directly affect player experience. Games may evolve and adapt to the player in many different ways and convey emotions through a variety of techniques and effects. Any adaptation process that will eventually close the affective interaction between the player and the game should be able to decide which stimulus (or playful experience) will be presented next when it should be presented, which actionable game elements should be adjusted, and how [8], [129], [130]—for a recent survey on biofeedback interactions, see [12]. Viewing affect-based adaptation from a high-level perspective, it appears that the game can adjust its agents—(or nonplayer characters) if those are available—or adjust its content to the affective needs of its player(s). Both of these actionable in-game element types can be manipulated in ways that lead the player to become more emotionally involved with the game. We review these categories in the remainder of this section.

A. Agents

Several games feature agents or nonplayer characters that may act as opponents, collaborators, or assistants [10]. Independently of the type of agent and its role such agents might be required to express emotion during their interaction with the player(s) and elicit specific emotional patterns. Emotion expression can be achieved in a completely scripted manner (e.g., behavior trees) all the way to machine-learned behavioral generation approaches (e.g., procedural personas). Approaches may rely upon popular emotion agent architectures [131], [132], [133], underlying cognitive models [134], or personality trait models [135].

It is important to note that emotion modeling plays a dual role when it comes to game agents: emotions both guide an agent's decision-making capacities, but they also affect the expressions of different emotional states (e.g., fear or sadness). Procedural animation is key for the latter with several impressive breakthroughs achieved for real-time animated characters [136] via generative systems [137].

B. Content

Not all games feature nonplayer characters, but all games have some form of content such as visuals, audio, game rules, game levels, and narrative; those content types can be defined as the creative facets available in games [5]. An affect-driven adaptive process could in principle alter those creative facets independently or in an orchestrated manner [6], [10]. The area widely known as procedural content generation (PCG) has offered several methods varying from simple search-based methods [138] all the way to deep-learning-based approaches [139] for the task. Of particular importance for the scope of this article is the experience-driven (ED) PCG framework [128], [140], which views game content as an indirect building block of player affect and proposes mechanisms for synthesizing personalized game experiences. Game content adaptation that may affect the emotional patterns of players can take the form of game rules [141], difficulty [142], lighting [143], camera profiles [62], maps [144], levels [145], tracks [146], narrative structures [147], and music [129]—among many other content types.

C. Indicative Examples

Affect adaptation in the games industry usually takes the form of dynamic difficulty adjustment (DDA) [10], [149], [150]. In DDA, certain agent properties (e.g., enemy's health, speed, and position) are predominately altered to match the skill of the player. Rubber banding in racing games (e.g., in the Forza series mentioned earlier) and difficulty scaling in games such as the Resident Evil series (Capcom, 1996–2023) are among the most popular methods for DDA in the games industry. While adaptation in games considers primarily a player's behavior, there are games such as Left 4 Dead (Valve, 2008) that follow the ED PCG [128] paradigm and, thereby, consider aspects of in-game tension and player's emotional intensity to adapt the game [151]. The game's AI Director observes the players' performance, follows a predetermined tension curve, and modifies the in-game experience by altering a number of content types: the number and location of opponents (zombies), and the pacing of the game and audiovisual effects.[3] The AI Director of Left 4 Dead (Valve, 2008) defines a seminal use of adaptive AI in games, and since its introduction in 2008, it has found multiple uses across games such as the Far Cry series (Ubisoft, 2004–2021) and Watch Dogs 2 (Ubisoft, 2016).

As an indicative research example in affect-driven adaptation, we will cover ED PCG via RL or EDRL for short [152], [153]. EDRL is able to generate various facets of game content (e.g., game levels and gameplay patterns)

[3] A video detailing the core aspects of the AI director is available here: https://www.youtube.com/watch?v=Mnt5zxb8W0Y.

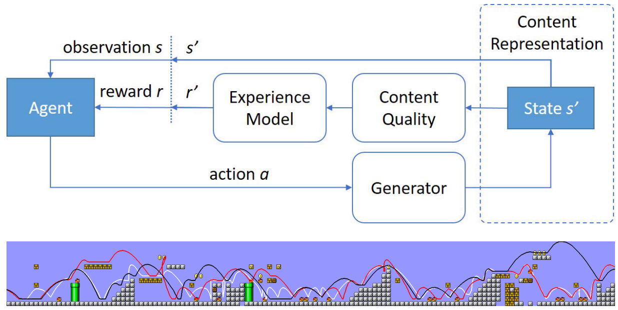

Fig. 8. ***ERDL framework (top) and an example of a Super Mario Bros level it generates (bottom). The play traces of three dissimilar agents are overlaid on the level. EDRL moderates the divergence of game level and gameplay based on Koster's theory of fun [148] and it designs levels endlessly via RL algorithms.***

that follow particular experience patterns via RL methods (see Fig. 8). More specifically, the method was applied for the online and endless generation of game levels and gameplay patterns in the game of Super Mario Bros. Inspired by Koster's theory of fun [148], reward functions were formulated as moderate degrees of level or gameplay divergence. The resulting multifaceted EDRL is not only capable of generating fun levels efficiently but is also robust with respect to dissimilar playing styles and initial game-level conditions.

VII. HOLISTIC VIEW OF AFFECTIVE GAME COMPUTING

This section provides a holistic overview of the field of affective game computing, focusing on state-of-the-art research, active areas, and research gaps in the field. Beyond the survey above, here we aim to show key examples of research across each phase of the affective loop. While our survey gave an overview in light of the larger field of AC and user modeling, our holistic overview highlights papers with a videogame focus. First, we outline the methodology we used (Section VII-A), and then, we analyze our findings (Section VII-B).

A. Methodology

Sections III—VI pull knowledge from the last two decades of research in affective game computing. This section, instead, complements our literature review with a survey of recent papers (i.e., past four years) from the primary publication venues of affective game computing research: the IEEE Transactions on Games (ToG) and IEEE Transactions on Affective Computing (TAC) journals, and the IEEE Conference on Games (CoG), the Conference on the Foundations of Digital Games (FDG), the Computer–Human Interaction in Play Conference (CHI-Play), and the Conference on Affective Computing and Intelligent Interaction (ACII).

Table 4 shows the outcome of this survey complemented with seminal works over the last 20 years of affective game computing. Table 4 is organized based on the core aspects

Table 4 Summary of Surveyed Studies Associated With the Four Core Phases of the Affective Game Loop—Elicitation, Sensing, Detection, and Adaptation. The Studies Are Placed Under Each of the Four Phases Based on Their Primary Focus Within the Affective Loop. They Are Also Placed Under One of the Main Categories of Each Phase Based on Their Research Emphasis

Phase	Category	Papers
Elicitation	Context	[14] [15] [20] [28] [32] [154] [155] [156] [157]
	AI Agent	[16]
	Content	[6] [13] [17] [18] [19] [23] [36] [158]
Sensing	Gameplay	[8] [42]
	Physiology	[11] [12] [46] [47] [61] [159]
	Camera-based	[48] [68] [71]
	Verbal & Speech	[81] [160]
	Subjective measures	[4] [95] [161]
Detection	Classification	[45] [106] [107] [115]
	Preference Learning	[25] [102] [108] [163]
	Reinforcement Learning	[44] [120] [122] [123] [126]
Adaptation	Content	[63] [88] [129] [130] [138] [139] [142] [143] [145] [147] [152] [153] [163]
	Agents	[137] [164]

of the affective game loop—elicitation, sensing, detection, and adaptation. While many of the presented papers utilize multiple—if not all—aspects of the affective loop, we have selected papers that focus on a specific phase of the loop with the corresponding high-level categories defined in Sections III–VI of this article.

B. Analysis of Findings

In this section, we discuss overall observations regarding the papers identified under each one of the four main phases of the affective loop (Table 4). Elicitation encompasses papers that focus on the emotional impact of games and their measurement. We divided these papers based on the game facet they considered. While many studies seem to put an emphasis on the game context, most of them focus on specific genres and platforms. In particular, the horror genre [15], [17], [154] provides a popular research test bed, possibly due to the visceral emotions that emerge while consuming horror media. VR and AR games are also popular for studying the impact of gameplay context on player experience [20], [155], [156]. Even though there are some studies dedicated to the ways the action space of the game affects the player experience [14], [28], there are no studies found that focus on the impact of the number of players, observability, stochasticity, and time granularity on player affect. When it comes to AI agents, there is surprisingly little research dedicated on how these agents can be used for emotion elicitation despite the field of believable nonplayer characters [165], [166] being very active. Unsurprisingly, most studies with a primary focus on affect elicitation are investigating the impact of the game content and the game environment [13], virtual objects [19], sounds [18], game events [28], or multiple facets of content [6] on affect elicitation. Summing it up, it appears that there are two major research gaps identified in game affect elicitation. First, there is lack of fundamental research into how components of the game context affect the player experience. Second, there is an untapped opportunity to utilize the research that has gone into creating more emotive and human-like agents for emotion elicitation in affective game computing studies.

Sensing appears to be a well-researched phase, with a special focus on physiology and peripheral signals (e.g., [11], [12]). Similarly, due to the ubiquity of web cameras, camera-based methods are also popular [48], [68]. While gameplay on its own can be a strong predictor of the player experience—and it is often the only modality available in the wild [42]—most studies in affective game computing aim for a multimodal approach instead. Finally, the field of voice-based sentiment and emotion analysis is overshadowed by more traditional user modalities such as physiological signals. This latter finding is surprising as in the world of eSports [160] and streaming services, and access to player voice and commentary is easier than ever. Regarding subjective measures, game affect sensing appears to adapt traditional AC labeling techniques to games—from annotation tools [89], [110] to Likert-like surveys [95]—but there is relatively little research effort put on the design of game-specific annotation tools—with VR and AR platforms being the exception [167] due to the involvement required from players.

Almost all studies presented involve some form of detection as it is the machine learning aspect that often aids the evaluation of other components of the affective loop. Most studies with a primary focus on detection traditionally involve supervised learning. While regression is still used from time to time for predicting aspects of player behavior (e.g., purchase decisions [168]), when it comes to affect modeling, the vast majority of the surveyed research studies have a preference for classification methods. This is despite a long line of research advocating for the ordinal processing and modeling of emotions [97], [98]. More interestingly, we observe a contemporary increase of interest in affect-driven RL [120], [122], [123]. Seeing how imitation learning algorithms are already being used in the games industry (see Section V-B about Forza Motorsport), we expect a rapid growth of interest in RL-based affect detection.

Finally, we take a look at studies mostly linked to the phase of adaptation (the bottom row of Table 4). One could argue that most commercial games that use some type of player-based adaptation employ a form of the affective loop. Similarly in academia, the research area of game affect adaptation is getting some serious traction in recent years. As shown in Table 4, there are plenty of research projects that focus on affect adaptation and intelligent interaction based on sensing and emotion detection. Unsurprisingly, similar to studies focusing on elicitation, most studies involving game affect adaptation focus on the game content instead of interactive agents [137]. While the holistic approach of ED PCG allows for more in-game adaptation opportunities [128], the lack of emotive agents in affect adaptation reveals a notable gap in the research field. Despite the successful affect-adaptive methods showcased in the literature, the widespread adoption of these techniques in commercial-standard games is still in its infancy. One of the biggest obstacles in this regard appears to be the field's reliance on often intrusive biosensors. While most physiological sensors can provide valuable multimodal data, such data are often very hard to reliably capture in the wild. We expect that future research avenues will investigate methods that would allow rapid deployment in games via camera-based technology or via the use of user-agnostic models—e.g., learning from in-game footage pixels or via privileged information [34], [35].

This section completes the survey and taxonomy of affective game computing. In the second part of this article (as initiated in Section VIII), we survey the tools available for reliable data collection in games and review the various game affect corpora that are currently available (Section IX).

VIII. COLLECTING AFFECTIVE DATA IN GAMES

Many tools for AC research can support games user research applications; however, games impose a number of unique challenges. Indicatively, different gaming interfaces provide different affordances both for play and data collection. Therefore, any dissimilarities across game controls and platform configurations would likely yield discrepancies in the collected telemetry and peripheral signals. Keeping a focus on affective data collection, the remainder of this section provides an overview of popular gaming interfaces (see Section VIII-A and available tools for sensor data collection (see Section VIII-B) and annotation (see Section VIII-C).

A. Gaming Interfaces and Telemetry

When it comes to selecting a game interface for an affective game computing experiment, there are several aspects that need to be considered. Desktop computers provide the most straightforward way of data collection. Since players have to be seated in front of a computer—operating with a keyboard and a mouse—they are generally less obstructed. This makes desktop setups ideal for laboratory studies. Designing and running experiments from a desktop computer also implies an easier integration between the experimental games and the research software. Due to the generally similar setup, crowdsourcing methods for data collection can be relatively reliable. On the flip side, desktop computers come in many different hardware configurations, which can affect the game performance, user experience, and quality of the data. Some of the available consoles, instead, such as the Microsoft XBox,[4] the Sony PlayStation,[5] and the Nintendo Switch,[6] include specialized gaming hardware. Due to the standardized hardware and software, the collection of data related to player experience on these platforms can be more consistent. These specialized systems, however, also pose a major limitation as it is generally hard to integrate console software with research-based hardware such as biosensors; the latter has often to be operated from a separate desktop computer.

As both desktop and console games are generally played by sitting in front of a monitor, the collection of traditional in-game behavioral telemetry, facial features, eye tracking information, and biosignals is relatively easier. In contrast, games that require full body movement are harder to integrate with more intrusive biosensors—especially the ones that involve electrodes and wires. Nevertheless, these games (and the platforms they are played on) provide unique affordances. Due to advances in computer vision and wearable technology, several exer, VR, and mobile games already integrate peripheral sensors into their systems.

Mobile games use regular smartphones as their platform. Due to the interactions afforded by these phones, the collected telemetry can cover an input space different from traditional consoles and desktop computers—such as tapping patterns and gestures. Many smart accessories are readily interfacing with smartphones, making it easy to collect peripheral data from different biosensors—such as photoplethysmography obtained via a smartwatch. The drawback of the platform is the uncertainty and obfuscation of the gameplay context. Notably, mobile games usually are played across many different environments for very short periods of time or with irregular breaks during the experience.

Exer(cise) games exist on both console and mobile platforms. They usually rely on peripheral sensors that collect body movement and biosignals [20]. The particularity of such games with regard to affective game computing is that they often employ a number of sensors to capture various modalities of the player. As players of exergames tend to (and have to) move their body throughout the game, the placement and arrangement of any physiological sensor poses a major challenge. Beyond the obstructed play, the motion and experimental artifacts that are embedded in the collected data make data cleaning and processing a nontrivial task [169].

[4] https://www.xbox.com/
[5] https://www.playstation.com/
[6] https://www.nintendo.com/switch/

Beyond console, desktop, and mobile platforms, VR and VR platforms—which become increasingly popular over the last few years—open a promising avenue for rich multimodal data collection in games; the Apex of Fear (2022) project covered earlier is one such example. VR Headsets, such as the Meta Quest,[7] Valve Index,[8] HTC Vive,[9] and HP Omnicept headset,[10] may provide a unique 360° immersive experience [156]. The VR headsets available generally block almost all obstructions coming from the physical environment and many can be used for multimodal data collection, including gaze and physiology (see more discussion in Section X).

Generally speaking, affect data collection based on passive affect elicitors, such as images, is usually combined with signals obtained via physiological and other peripheral sensors. In games, however, it is a dominant practice to collect data from in-game telemetry in addition to any other sensor data and independently of the game platform used. This type of behavioral data can be very powerful, especially in multimodal applications. The form of such data, however, highly depends on the given game and purpose of collection. While some game engines offer standardized methods to collect various types of user data, these methods often focus on data relating to monetization (see, e.g., the Unity Analytics[11]).

B. Sensing Devices and Tools

One of the most comprehensive surveys of AC research and development tools to date shows that even though there is a continuous development of new tools, most studies end up using custom-made solutions [170]. This is also largely true for data collection, labeling, data processing, and machine learning platforms and tools, and it makes intuitive sense, especially when it comes to collecting data from games.

Collecting physiological sensor data is typically achieved through a vendor-based solution. The market is filled with reliable solutions for EEG, EDA, HR, and eye-tracking sensors. Some of the popular vendors include Emotiv,[12] Empatica,[13] Intel Realsense,[14] Plux,[15] Polar,[16] Shimmer,[17] and Tobii,[18] among many others. Most of these vendors offer processing software as well, although open-source solutions do exist. A recent survey on the field of affective game research showed that the most popular modalities employed include heart activity, followed by facial recognition and EDA [11]. Beyond specialized sensors, conventional cameras are also often used to collect recordings of subjects. Vendor-based solutions exist to process such multimodal data (i.e., Affedex [171] for facial recognition); researchers, however, may prefer to use open-source tools such as OpenCV[19] for general computer vision tasks or OpenFace [172] for facial recognition.

While most AC methods can be transferred to game research without any major hiccups, sensing technology, in particular, brings two core challenges to the table. First, playing is usually physically active—even if the user plays on traditional platforms using a controller—which means that any sensor used for data collection has to afford a degree of comfort and free movement. Second, because games generally impose a high level of cognitive load on the user, there is an expected loss of affect expressivity. Due to this limitation, some more popular detection methods—such as face-based affect recognition—might be less relevant when applied to games [173], [174].

C. Annotation Tools

In this section, we review the available annotation tools that could be used for collecting affect labels in games. We also discuss the appropriateness of these tools for affective game computing. Table 5 summarizes our survey on popular annotation tools that were introduced during the last two decades.[20] One of the major trends of the AC field is the shift from discrete and more complex annotation methods toward simpler, continuous labeling techniques. Early annotation tools, such as ANVIL [176] or ELAN [177] (released in 2001 and 2006, respectively), focused on measuring discrete categorical emotions. While the natural language processing field still uses such tools for labeling speech and text and certain annotation software still offers categorical labeling options (i.e., NOVA [185]), the field of AC started to shift away from such tools relatively early. With the advent of machine learning, moment-to-moment affect modeling became feasible—and with it, continuous annotation tools started to be used more widely. Traditional annotation tools, such as FeelTrace [175] (released in 2000), AffectButton [179] (first released in 2009), and AffectRank [161] (released in 2015), measure multiple dimensions of affect at once—in some cases up to three dimensions. Annotation tools of that period were inspired by the circumplex model of emotions [187] and generally used to label the arousal–valence–dominance spectrum.

While the 2-D annotation scheme is still popular nowadays, we note a shift toward 1-D labeling tools (from 2013 onward), including GTrace [181] (released in 2013), ANNEMO [180] (released in 2013), CARMA [182] (released in 2014), RankTrace [183] (released in 2017), and PAGAN [110] (released in 2019). Similar to FeelTrace in multidimensional labeling, GTrace became the new foundation for 1-D annotation tools. The bounded,

[7]https://www.meta.com/quest/products/quest-2/
[8]https://store.steampowered.com/valveindex
[9]https://www.vive.com/
[10]https://www.hp.com/us-en/vr/reverb-g2-vr-headset-omnicept-edition.html
[11]https://unity.com/products/unity-analytics
[12]https://www.emotiv.com/
[13]https://www.empatica.com/
[14]https://www.intelrealsense.com/
[15]https://www.pluxbiosignals.com/
[16]https://www.polar.com/
[17]https://shimmersensing.com/
[18]https://www.tobii.com/
[19]https://opencv.org/
[20]N/A indicates that an installer is "not-available."

Table 5 Review of Annotation Tools

Tool	Dimensions	Label	Installer
FeelTrace [175]	2 dimensions (arousal-valence)	bounded continuous circumplex	N/A
ANVIL [176]	Categorical labels	discrete labels	Standalone installer
ELAN [177]	Categorical labels	discrete labels	Standalone installer
EmuJoy [178]	2 dimensions (arousal-valence)	bounded continuous	Standalone installer
AffectButton [179]	3 dimensions (pleasure-arousal-dominance)	bounded continuous	Standalone or online
ANNEMO [180]	1 dimension (configurable)	bounded continuous	Node.js package
GTrace [181]	1 dimension (negative to positive)	bounded continuous	N/A
CARMA [182]	1 dimension (negative to positive)	bounded discrete (configurable)	Installer (requires MATLAB[20])
AffectRank [161]	2 dimensions (arousal-valence)	discrete circumplex	Adaptation through PHP and JavaScript
RankTrace [183]	1 dimension (tension)	unbounded continuous	C# source (pre-built version available; requires VLC[21])
DARMA [184]	2 dimensions (configurable)	bounded continuous (optional circumplex)	Installer (requires MATLAB, VLC, and a joystick)
NOVA [185]	1 dimension or categorical (configurable)	bounded continuous or discrete labels	Standalone installer
PAGAN [110]	1 dimension (configurable)	unbounded and bounded continuous and discrete binary (configurable)	No installation (online)
RCEA [186]	2 dimensions (arousal-valence)	bounded continuous circumplex	N/A
RCEA-360VR [167]	2 dimensions (arousal-valence)	bounded continuous	Python package

continuous annotation method quickly spread and became popular in human–computer interaction and AC studies [188], [189], [190], [191]. The first new annotation method to break the mold was RankTrace, with an unbounded protocol aimed to collect data specifically for preference learning [183]. Nevertheless, GTrace and its derivatives remain one of the most popular annotation tools to this day.

The core strength of 1-D labeling tools is the reduced cognitive load they cause to annotators compared to multidimensional labeling in which annotators are requested to split their attention [181] across multiple dimensions and labels. Focusing on one affect dimension at a time reduces noise and provides a higher face validity. Multidimensional tools, however, can produce annotations at a higher rate. Moreover, as labels across different dimensions are collected simultaneously, the labels are less susceptible to recency effects [192] compared to those obtained from repeated 1-D protocols. For all aforementioned reasons, multidimensional annotation methods are still popular today. Meanwhile, a series of new such tools have been developed recently, including DARMA [184] (released in 2018) and two versions of RCEA [167], [186] (the original was released in 2020 and the VR version was released in 2021).

Another, even more recent, trend is the shift from annotation tools that are usable in a lab setting toward those that are usable in the wild. Many traditional and popular tools require researcher oversight, which limits the dataset size collected. In addition to this issue, the new social reality brought on by the COVID-19 pandemic pushed the field even more toward crowdsourcing affect labels. PAGAN [110] is one of the first frameworks developed with crowdsourcing capacities in mind. Compared to earlier annotation tools, PAGAN is highly configurable and supports multiple different annotation techniques, including a GTrace and a RankTrace variant. While PAGAN tackles the issue of crowdsourcing by using an online platform, other annotation tools offer mobile integration (RCEA [186]) and VR integration (RCEA-360VR [167]) or aim to alleviate the need for annotators through automatic labeling (NOVA [185]). We can observe this shift toward crowdsourcing and mobile integration in custom, yet-to-be-released annotation tools as well [193], [194], and we expect more reliable crowdsourcing methods to appear as the focus will continuously shift from the lab to real-world (in the wild) experiences.

IX. GAME AFFECTIVE CORPORA

Instead of building a new affect corpus from scratch, one may apply AC methods directly to existing corpora. Unlike traditional AC datasets, however, player modeling research often focuses on player experience aspects that are not directly linked to affect. Many player experience datasets for instance are annotated with high-level game-related concepts, such as frustration, perceived challenge [62], [195], engagement [195], and fun [62], [196]. Nevertheless, AC methods are still applicable; and conversely, such datasets can offer interesting new test beds for AC applications. This section reviews a number of available affect corpora that are built using games as the underlying context of interaction.

While, traditionally, AC datasets are collected through induced emotions and posed expressions, in recent years, we have witnessed a notable shift toward spontaneous emotion elicitation and naturalistic settings. During the last decade, a new wave of datasets has started to employ popular multimedia as elicitors of affect [197], [198], [199]. Using artifacts such as clips and still images from popular movies has proven to be a reliable and cost-effective way to elicit emotions in a natural way. The resulting datasets, however, only focus on a specific type of passive elicitation that comes with consuming traditional media. The latter half of the decade, instead, has seen a rise in affect corpora that employ interactive elicitation methods, including dyads [180], [200], group tasks [201], board games [202], and videogames [32], [195], [196].

There are two major differences one can identify between traditional AC and game-based corpora. The first difference is that traditional AC corpora use third-person annotation (i.e., RELOCA [180], LIRIS-ACCEDE [203], Aff-Wild [198], AffectNet [199], and SEWA DB [200]) whereas game-based datasets, instead, use primarily self-reports (i.e., MazeBall [62], PED [195], FUNii [196], MUMBAI [202], and AGAIN [32]). The second major difference between AC and player experience datasets is the wider focus of the latter on experience aspects that often cover behavioral or user states. In fact, most player experience datasets do not consider affect labels or affect manifestations at all. While there is definitely a mapping between affect and higher level concepts such as fun and engagement, revealing that such a relationship might not be as trivial. With this in mind, the survey of datasets presented in this section focuses on game-based datasets that have some connection to AC; in particular, they either consider physiological signals and/or are annotated using traditional affective dimensions such as arousal or valence. For the sake of clarity, we also omit datasets that might have been influential in the past but are not available anymore—such as the Tower Game [204] or the GeMo [205] datasets—and popular game-based datasets that do not include affective labels—such as the Obstacle Tower dataset [206].

Table 6 presents our survey of 11 datasets, which can be used for affective game computing research. Most of the datasets presented here are quite recent (i.e., eight of 11 are released in 2019 or later) showing the potential and the emerging nature of the field. Moreover, most of the examined datasets focus on one specific context, i.e., the genre of the game. While the AGAIN dataset [32] was designed explicitly to offer a wide array of different games, the Atari-HEAD [210] and MUMBAI [202] datasets also provide more varied inputs in their own niche (arcade and board games, respectively). Many game datasets contain video data of the gameplay footage, which is ideal for deep learning applications and for mapping pixels to affect directly [33], [34]. While pixel-based affect detection might be a harder task on datasets collected on board or social games (i.e., MUMBAI [202] and GAME-ON [201]), datasets that provide a large amount of gameplay footage are ideal for computer vision methods (i.e., Atari-HEAD [210] and AGAIN [32]). Five out of the 11 affective game computing corpora feature physiological signals that are more commonly used in traditional AC research, while only three of them feature eye-tracking data. In addition to traditional features, many game datasets (five of the 11 surveyed) contain behavioral and contextual data in the form of game telemetry and player input. This type of data has proven to be robust as a predictor of game-related emotional states [4], [162], [212].

Even though all datasets surveyed contain multiple modalities of user signals, not all of them offer affect labels. Specifically, three of the surveyed datasets (i.e., GSET Somi [207], eSports Sensors Dataset [209], and Atari-HEAD [210]) do not provide affect labels of any sort. The rest of the corpora provide a wide array of experience labels, mostly related to high-level game-related outcomes such as fun, challenge, and engagement. Two of the surveyed datasets feature emotional labels (GAME-ON [201] and IRAFFE2 [211]), whereas three of them contain at least one type of affective label (RAGA [208], MUMBAI [202], and AGAIN [32]). As mentioned earlier, affect labels in games are predominately self-reported and not usually annotated by a third person.

Reflecting over Table 6, one can observe a substantial increase in interest and availability of game-based datasets over the last few years; there are still, however, many aspects of player experience that have not made it to an affect corpus as of yet. Moreover, the design of the various data collection protocols comes with limitations. Most notably, the wide spectrum of labels used across the corpora makes it hard to compare datasets and transfer any knowledge gained across corpora. While it is understandable that game-related outcomes are more important than basic affective dimensions for game user researchers, some level of standardization would go a long way toward making these datasets more accessible and reusable. Nevertheless, affective corpora—as the ones surveyed in Table 6—that are based on interactive elicitation bring a new perspective to AC at large, as such elicitation methods were largely unsupported by traditional datasets up until recently.

X. CONSIDERATIONS AND DISCUSSION

After surveying the affective game computing field as a whole, the available tools for data collection, and finally the datasets available, in this section, we will discuss a number of considerations that are linked to this field. Specifically, we will start by outlining a number of ethical considerations and we will then briefly touch upon the current hardware limitations that can be detrimental to research advancements and breakthroughs in the field.

A. Ethical Challenges

With the acceleration of widespread AI adoption, various ethical considerations around the field have become more important than ever. While, on the one side, we can observe an unprecedented increase of AI use in both academia and industry, on the other side, we can see

Table 6 Affective Game Computing Datasets. "N/A" Indicates That a Category Is "Not-Applicable"

Database	Game Type	Games	Video (hours)	Participants	Modalities	Annotation	Labels	Annotators	Tasks
MazeBall [62]	Navigation	1	N/A	36	BVP (HRV), EDA, game telemetry	Pairwise	Fun, challenge, frustration, anxiety, boredom, excitement, relaxation	self-report	1
PED [195]	Platformer	1	6	58	Gaze, head position, game telemetry	Discrete (5-step), pairwise	Engagement, frustration, challenge	self-report	1
GSET Somi [207]	Rail Shooter	1	6.75	84	Eyetracking, gameplay video	N/A	N/A	N/A	1-3
FUNii [196]	Action	2	N/A	190	ECG, EDA, gaze and head position, controller input	Continuous, discrete	Fun (cont.), fun, difficulty, workload, immersion, UX	self-report	2
RAGA [198]	Racing (VR and PC)	2	N/A	33	ECG, EDA, EMG, resp.	Continuous bounded	Arousal, valence	self-report	2
GAME-ON [201]	Escape room	1	11.5	51	Video, audio, and motion capture data	Discrete (5–9-step)	Emotions, cohesion, warmth, competence, competitivity, leadership, and motivation	self-report	5
eSports Sensors Dataset [199]	MOBA	1	N/A	8	EEG, BVP (HR), EDA, EMG, temp., hand and head gestures	N/A	N/A	N/A	11
Atari-HEAD [210]	Arcade	20	117	4	Eyetracking, gameplay video, game telemetry	N/A	N/A	N/A	20
MUMBAI [202]	Board-game	6	46	58	Gameplay, facial video, and facial action units	Discrete labels	Valence, attention, gameplay experience, personality	56 (3^{rd}-person) 58 (1^{st}-person)	6
BIRAFFE2 [211]	Platformer, navigation	3	23	103	EEG, EDA, game video, game telemetry, facial recognition	Continous (automated) and discrete (survey)	Emotions, NEO-FFI and GEQ survey	automated (emotions), self-report (survey)	3
AGAIN [32]	Racing, shooter, platformer	9	37	124	Game video, game telemetry	Continuous unbounded	Arousal	self-report	9

the growing public anxiety toward the very same systems [213], [214]. Although many ethical frameworks exist to address these anxieties, the industry as a whole has been slow to react [215]. This section highlights some of the challenges in responsibility, transparency, auditability, incorruptibility, and predictability [216] that future game affective applications will have to face [217], [218]. The interested reader may refer to [219] for a recent in-depth discussion of ethical considerations related to the various uses of AI in and for games.

The first challenge is to establish a well-defined chain of responsibility and ownership over affect models, the data they train on, and their output. A major issue in this topic is the decoupling of the data, the model, and its output. Because the results provided by an affect model are thought to be "inferred" instead of "observed," the chain of responsibility becomes opaque [220]. Even though the responsibility of transparent data handling is well-defined in documents such as the European Union's General Data Protection Regulation (GDPR) [221], the research community is still lagging behind [222]. The issue is not trivial both on the academic and industrial levels by the fact that affective corpora—despite being deeply personal—is not protected under the current legal frameworks [215]. We already note proposals for a change in regulations [223] addressing some of these issues and expect future affective interaction applications to be upheld to more scrutiny.

Transparency is a core challenge of AI as a whole. While seemingly a clear-cut issue, which can be tackled by explainable AI systems [224], [225], in reality, the issue is complicated by the transparency–efficiency tradeoff [226]. This phenomenon describes the detrimental effect of bias against AI [227] to human–machine cooperation. Resolving transparency in games is even more challenging due to the "smoke and mirrors" nature of the medium.

Auditability is more of an industry-specific challenge rather than an academic one, as recent research studies already strive for external validity and reliability. Industrial applications of affective game computing should consider the audit process during their development cycle. As the field moves more and more toward large-scale foundation models [228], the role of planned audits to maintain transparency will become more and more a necessity.

The challenge of Incorruptibility refers to the robustness of the system against any kind of manipulation. While short-lived research-focused projects are generally not expected to receive many adversarial attacks—if any; industry applications and even large-scale crowdsourced studies have to face external attackers. However, beyond malicious users, computer models can also be corrupted by internal forces. Biased affect models can encode and perpetuate socioeconomic and sociopolitical biases that lead to direct or indirect harm to the users [229], [230], [231]. Unfortunately, incorruptibility is a wicked problem in the field as often there is no apparent way of ascertaining algorithmic bias before the system is deployed.

The final challenge for ethical AC applications is predictability. Similar to auditability, academic studies in general fare well on this front because predictability is somewhat analogous to the internal reliability and validity of the system. Beyond this, predictability can help increase transparency and incorruptibility by ensuring the reliability and fairness of the application in question [232].

The framework presented here as adapted from [219] describes the universally understood challenges when it comes to AC applications in games. These issues have served as a bedrock for discussions and proposals surrounding ethical player modeling [217], ethically aligned design [233], ethics in human–AI interaction [232], AI trustworthiness [234], and general ethical AI guidelines [235].

B. Hardware Limitations

As already mentioned in Section VIII, sensing affect via objective measurements offers rich information about the player's experience; a major limitation, however, is that several of these sensors can be invasive, impractical, or even impossible in the wild. Pupillometry and gaze tracking for instance are sensitive to variations in light and screen luminance. Camera-based sensing (e.g., facial expressions and body posture) requires a well-lit environment, which is often not available when we play videogames in our living rooms for instance. However, the recent rapid advancement of mobile, smartwatch, and VR hardware with integrated eye tracking and physiology sensors (e.g., see the recent HP Omnicept headset) gives such sensing technologies entirely new opportunities and uses within games [236]. Speech and text may offer some alternative unobtrusive and highly accessible modalities that are only applicable, however, to games that feature those modalities. This includes games in which speech is a control modality [237], [238], text is used as means of communication across the audience of a streamed game [4], speech or chat is used for multiplayer coordination, and natural language processing is used as a game control in text-based adventure games or interactive fiction. Finally, existing hardware for EEG, respiration, and EMG (if not embedded within a VR headset) requires the placement of sensors on the player's body, thereby making those physiological signals intrusive and rather impractical, to say the least. Recent sensor technology advancements, however, especially via state-of-the-art VR headsets (see Section VIII) have revived the use of physiological signals for commercial standard applications [52].

XI. ROAD AHEAD

In this section, we will cover the two areas we think will be the most challenging for future research in affective game computing. In particular, we first discuss current and future research in the area of artificial general intelligence (AGI) and emotion in games, and we move on to discuss particular computer vision research areas that appear to be of high value for affective game computing research. We end with a small section dedicated to LLMs and their potential impact on affective game computing.

A. AGI and Affective Game Computing

Damasio's work [239] suggests that our ability to recognize human emotion across contexts and people of dissimilar moods, cultural backgrounds, and personalities acts as a facilitator of decision-making and general (emotional) intelligence [240]. While the research reviewed has reached important milestones, all key findings suggest that any success of affective (game) computing is heavily dependent on the domain, the task at hand, and the context in general. This limitation of specificity is also present in games [8]. The vast majority of the studies presented focus on modeling player experience within a particular game and a narrow player base, and under well-controlled conditions (e.g., [128], [174], [241], and [242], among many others).

Assuming that the game affective loop can be successfully realized within a particular game, the next long-term and ambitious goal for affective game computing is to achieve a good level of generality across games of the same genre of other genres. For affective game computing to become general, models are required to recognize general emotional and cognitive-behavioral patterns across contexts of players and games. So far, the literature is rather sparse in this area with only a few available preliminary studies. Early work focused on the ad hoc design of general metrics of player interest for prey–predator games [243], [244] followed by player experience models that can operate to a satisfactory degree across dissimilar games [31], [245], [246]. Recent work in the area is driven by the AGAIN dataset [89] through which a number of promising studies have been performed to test for the generality of player arousal models across games [32], [247]. Discovering entirely new representations of player emotive manifestations across games, modalities, and player types appears to be a critical step toward achieving general player affect models. Methods from representation learning and transfer learning could be of great assistance to this cause [247]. In Section XI-B, we discuss how such computer vision methods can further advance the study of affective game computing.

B. Computer Vision for Affective Game Computing

Computer vision research brings methods with great potential for the future of affective game computing. Recent work in the use of convolutional neural networks has shown that it is possible to solely rely on gameplay footage and in-game audio for predicting player affect with high levels of accuracy [33], [34], [115]. What is fascinating about pixel-based affect modeling is that it is general and user-agnostic: it is general as it can eventually represent any affective patterns by observing the game footage pixels; it is user-agnostic as it does not rely on any other personal information about players beyond their gameplay (e.g., manifestations of affect via the physiology of facial expressions). These two properties make pixel-based affect models operational in the wild. Making players affect models usable in the wild is key for the models to be usable in games. A recent direction with great promise addressing the operation of affect models in the wild is the use of privileged information [35]. Privileged information allows models to be trained with game lab data (e.g., including physiology, speech, and facial expression) and operate without these modalities, which are not available in a player's living room (i.e., in the wild).

Complementary to the above computer vision methods, self-supervised learning (SSL) methods, such as contrastive learning, define a recent machine learning paradigm, which has been widely and successfully employed for learning general representations of data [248]. SSL methods attempt to learn by processing different views of the same input that have similar representations. Although contrastive learning is gaining traction for computer vision tasks, such methods have found applications in games [249], [250] and AC [251], [252] only recently. SSL-based affect modeling assumes that affect information is an inherent property of the manifestations of affect and thus can be fused and learned in a contrastive learning manner. Early results of Pinitas et al. [252] suggest that when affect is used as a label to contrast multimodal data, arousal models achieve supreme classification performance compared to end-to-end classification.

C. LLMs for Affective Game Computing

Large-scale language models, such as GPT-3 [93] and GPT-4 [94], appear to offer promising, yet largely unexplored, methods for affective game computing. We envision the use of LLMs for learning and interweaving game context and affect demonstrations as, e.g., in early experiments reported in [253]. In principle, an LLM that is hosted in a game engine could predict any affective state transition, including states where "the game is more engaging" and thereby change the surrounding environment or spawn a number of enemies to get the player to a supposedly more engaging state. Learning to generate affect transitions via foundation models builds on the ED PCG paradigm [128] but with a contemporary touch. Generative affect-based AI methods, including GPT variants and diffusion models [254], will likely expand beyond text-to-(affect)-image applications [255], to text-to-video, text-to-3D models, and finally text-to-games with prescribed affect patterns [253]; text can be replaced (or complemented) by other modalities, including images and sound.

Compared to the very specific game state transitions that an LLM could use to play a game, the relationship between game context and player affect appears to be more general [32]. One can thus argue that such relationships could potentially be learned from many games rather than one. We could then imagine the future development (or fine-tuning) of large foundation models that are capable of representing and inferring affect transitions based on in-game observations and affect demonstrations. Referring to our earlier discussion about AGI, it remains to be seen to which degree we can build a generalized computational game experience designer and how.

XII. CONCLUSION

The domain of games has advanced the ways we represent, model, and annotate emotion over the last decade. It is their highly interactive nature, the complex spatiotemporal and rich behavior of their users, and the availability of multiple sensor data that have helped such advancements collectively. AC has also advanced game design and development. For instance, affect-driven adaptation and automatic player experience design are becoming gradually the norm across a number of game genres (e.g., horror and racing). This article surveyed this exciting intersection of AC and games and introduced the field of affective game computing through the phases of the affective loop. This article also introduced a taxonomy of terms and methods used largely in affective game computing and placed exemplar studies on this taxonomy. Finally, this survey offers the interested reader a comprehensive list of data collection tools and datasets that are directly accessible for research in this field.

With this article, we survey the past, capture the present, and offer a vision about the future of this field. In our attempt, we tried to be as comprehensive and inclusive as possible (as indicated by the reference list of this article). Despite the best of our intentions, however, we are aware that some studies were omitted or not discussed thoroughly due to space considerations. Evidently, while a lot has been achieved in affective game computing until nowadays, there are still many open research questions left to be addressed. We hope that this article will act as a key driver of groundbreaking research and innovation in this emerging field. ■

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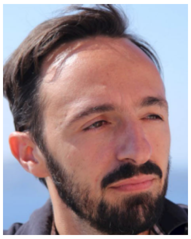

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