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A Survey on Affective and Cognitive VR

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Abstract—In Virtual Reality (VR), users can be immersed in emotionally intense and cognitively engaging experiences. Yet, despite strong interest from scholars and a large amount of work associating VR and Affective and Cognitive States (ACS), there is a clear lack of structured and systematic form in which this research can be classified. We define "Affective and Cognitive VR" to relate to works which (1) induce ACS, (2) recognize ACS, or (3) exploit ACS by adapting virtual environments based on ACS measures. This survey clarifies the different models of ACS, presents the methods for measuring them with their respective advantages and drawbacks in VR, and showcases Affective and Cognitive VR studies done in an immersive virtual environment (IVE) in a non-clinical context. Our article covers the main research lines in Affective and Cognitive VR. We provide a comprehensive list of references with the analysis of 63 research articles and summarize future works directions.

Index Terms—Virtual Reality – Affective Computing – Affective States – Cognitive States – Emotions – Mental Workload – Physiological Measures – Social and Behavioral Sciences

1 INTRODUCTION

VIRTUAL REALITY (VR) technologies enable users to feel "*present*" in a synthetic 3D scene simulated artificially [138]. This gives VR the potential to engage users in a virtual world and to be a strong emotional driver. At the same time, VR allows to simulate complex, realistic, and unrealistic situations while immersing users in a highly controlled and safe virtual world. This makes it an ideal media to induce, study and understand Affective and Cognitive States (ACS). Affective States (AS) refer to states such as emotions, moods, and feelings [132], and Cognitive States (CS) refer to states like cognitive load or mental workload, that influence how information is processed (e.g., reasoning, deliberation, planning) [22]. While there are some distinctions in their definitions and models, AS and CS are interwoven [78]. They have various similarities as multicomponent constructs [110, 132] and in the methods to measure them [103].

The interest in associating ACS and computers was raised early. In 1995, Picard et al. defined "*Affective Computing*" as a type of computing which "*relates to, arises from, or influences emotions*" [118]. They highlighted the fact that emotions can act as powerful motivators, influence perception, cognition, coping, and have an important role in creativity [118]. In that sense, giving computers the ability to recognize, express and have emotions could contribute to a richer quality of interactions, which is essential in VR. Similarly, taking into account users' cognitive abilities and limited cognitive resources [153] could make VR experiences more fitted to users. For these reasons, many researchers have shown their interest in associating VR and ACS by inducing, recognizing, and exploiting ACS in VR.

The adaptation of Immersive Virtual Environments (IVEs) by taking into account the user's ACS can be done following these steps (see Fig. 1): VR stimuli are presented to the user, which triggers AS and CS responses that can be assessed using different metrics (e.g., self-reports, physiological measures). Then, objective metrics can be used to recognize the user's perceived AS or CS in real-time using Machine Learning (ML) algorithms or rule-based models. Finally, this recognized or measured AS or CS can be exploited to modulate the IVE content. Such a process is not new as similar frameworks applied to emotions and games specifically [23, 82], outside VR [26, 71, 118], already exist. However, few studies went through the whole adaptation course in IVEs. Furthermore, no review currently summarizes the findings considering the different steps of the adaptation loop. Works that study ACS in VR usually treat at least one of these categories:

- The **induction of ACS** corresponds to the study, design, or development of content, parameters, or methods that can influence or induce changes in the users' ACS.
- The **recognition of ACS** corresponds to the study, design, or development of recognition models or methods to identify users' ACS.
- The **exploitation of ACS**, corresponds to the study, design, or development of feedback or adaptation methods, logic, and parameters based on users' ACS measures.

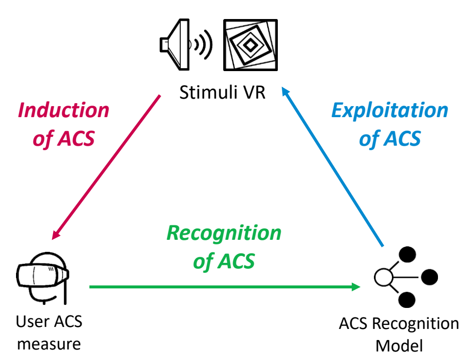

FIG. 1: Loop depicting the adaptation of VR based on users' ACS, as well as the categorization of Affective and Cognitive VR studies in the survey. Stimuli in VR first *induce* AS or CS responses to the user. Then, these responses are measured from the user, and used to *recognize* the user's AS or CS. Finally, the recognized AS or CS is *exploited* to adjust the VR stimuli and parameters.

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Based on this categorization, we propose to define "**Affective and Cognitive VR**" as "*the study of virtual reality systems and applications that induce, recognize, or exploit affective and cognitive states*". In this definition, AS and CS are grouped because of the similarities they share in the way they are processed in VR studies. However, this can be discussed as they can be differentiated in their concepts. In that case, works can speak of "*Affective VR*" when they relate to the study of AS, and "*Cognitive VR*" when they relate to the study of CS.

In this paper, we provide an overview of Affective and Cognitive VR studies performed in IVEs in a non-clinical context. The objective is to present the current findings in each induction, recognition, and exploitation of ACS in IVEs categories to go towards adaptive VR applications that consider the user's ACS. For reviews, meta-analyses, and strengths, weaknesses, opportunities, and threats (SWOT) in VR in the clinical context (e.g., therapy, pathological phobia), interested readers can refer to [27, 116, 120, 123, 125, 127]. Specific aspects such as interaction design for positive usages and the training field can also respectively be found in [70] and [156].

2 Methodology

We performed the following queries on Google Scholar and IEEE Xplore websites to collect the papers for this survey. Search criteria included all publications from 1999 to March 2020. The following keywords were used: ("virtual reality" OR "immersive virtual environments") AND ("affective state" OR "emotions" OR "personality trait" OR "mood" OR "anxiety" OR "cognitive state" OR "mental workload" OR "cognitive load" OR "cognitive performance" OR "psychological state" OR "physiological signals"). The inclusion criteria were: "written in English", "mentioning the use a VR Head-Mounted Displays (HMD) or a CAVE-like system", respectively considered as fully-immersive and semi-immersive systems [65], "measuring an AS or a CS or aiming to induce, influence, recognize, or exploit an AS or a CS". The exclusion criterion was "targeting clinical patients or clinical use cases". Upon completion of the search, titles and abstracts of the identified articles were assessed for suitability for the review following the inclusion and exclusion criteria. Then, the full texts of the articles were retrieved for further examination of their contents. They were independently reviewed, screened by the researchers, and classified into the proposed induction, recognition, and/or exploitation categories. Panoramic and 360° videos were included if they were displayed using immersive VR hardware (i.e., HMDs or CAVEs). Only works studying psychological states were retained. We excluded studies that focused on motor task performances and did not consider mental or cognitive tasks. Systematic reviews, meta-analyses, frameworks, and methodological approaches were also retrieved and examined. However, these works were excluded from the principal analysis. The references lists of the selected articles were reviewed for additional publications that might have been overlooked in the search. A resulting panel of 63 studies was retained in the scope of this survey, among which 43 studies deal with AS, 14 with CS, and 6 with both ACS.

3 Affective and cognitive states: Definitions and Models

In this survey, the focus is set on emotions and anxiety (AS), and cognitive load and mental workload (CS), as they are the main ACS studied in the VR community. There is no real consensus over the definitions of psychological states, and AS and CS can overlap in their definitions and in the methods to measure them [103]. Still, a way to differentiate AS and CS can be proposed based on the ways they are elicited and in the processes and responses they are going to provoke. On the one hand, AS mostly relate to primal instincts and derive from personality traits and personal experiences [17]. They can be manipulated, for instance, by stories, narrative content, and preferences, and they influence decision-making. On the other hand, CS derive from cognitive resources, cognitive skills, and influence how information is processed [22]. They can be manipulated, for instance, by the intrinsic difficulty of a task, the number of distractors, and the instructions presentation format. These will have consequences on the errors one will make and metrics such as the reaction time. The definition of an AS or a CS is mainly chosen depending on the field, the context, and the aim of the study [72]. While AS and CS are treated in similar ways in IVEs (see Fig. 1), the selection of an appropriate psychological model is crucial for the choice of the measurement method, and all the other steps in a research dealing with ACS [103].

In this section, definitions and models of emotions and anxiety will first be addressed, followed by those of cognitive load and mental workload. The occurrence of each ACS measured in the 63 studies retained in this survey is depicted in Fig. 4. Finally, findings on the link between ACS and presence will be presented.

3.1 Affective States

Affective states can be distinguished in terms of time (duration), intention (event focus), cause, and impacts on the behaviour and physiological responses among other criteria [18, 45, 132]. In particular, a distinction can be made between states and traits. States can be defined as a concurrent experience or transient mood while traits are more permanent. As such, eliciting a state too often can result in a trait change [141]. Among the different AS, emotions and anxiety are the most studied constructs in IVEs.

A well-accepted definition of **emotion** is given by Scherer [132]: "*an episode of interrelated, synchronized changes in the states of all or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism*" [131]. In his definition, the five organismic subsystems correspond to a categorization of the physiological responses. As for the emotional models, Kołakowska et al. [73] proposed to classify them into three categories following different perspectives:

- Emotions, from a **dimensional perspective**, are considered as continuous phenomena that can be represented in N-dimensional spaces, usually within two or three fundamental dimensions. Among the multiple models, Mehrabian and Russell [99] proposed a 3D environmental emotional scale of "*nearly independent bipolar dimensions*", abbreviated as PAD for Pleasure, also referred to as valence (from negative to positive), Arousal, which corresponds to the excitation, mental activation or level of alertness, and Dominance, which is the degree of feeling of having control over a specific situation. Another popular model is Russel's circomplex model of affect [128], which defines emotions based on two dimensions: the emotional valence on the x-axis and the emotional arousal, on the y-axis.

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- From a **discrete perspective**, each emotion is studied independently, as if all emotions were distinct. The most popular discrete category of emotions is the Facial Action Coding System (FACS [51]) one for expressions recognition: the Big Six (Happiness, Sadness, Fear, Anger, Disgust and Surprise). These fundamental emotions are considered innate, basic, and determined in both psychological and biological sense from this perspective. To this basic set, some added the Neutral expression [63] or extended it with other emotions such as Guilt, Pride and Shame, which have a more complex behavioural manifestation. Other sets of basic emotions are proposed and reviewed in [68, 107].
- Emotions can also be defined from a **hybrid perspective**, combining discrete and dimensional viewpoints. A good example is Plutchik hierarchical model [119] where complex emotions are combinations of pairs of more basic emotions.

Studying emotions from a discrete perspective is at first very simple and intuitive. However, it describes emotions without any inter-relationship, which makes the recognition of non-basic affective states more difficult. On the other hand, the dimensional perspective offers the possibility to study emotions as a function of continuous and nearly independent variables. However, this perspective tends to not be as expressive as the discrete perspective. The hybrid perspective was not used in VR studies to our knowledge yet, hypothetically because of its large panel of emotions.

As for other AS, **anxiety** has been of particular interest in the VR community, even more in VR exposure therapy. Spielberger defined anxiety as "*a complex emotional reaction or state that varies in intensity and fluctuates over time as a function of the intrapsychic or situational stresses that impinge upon an individual*" [141]. He made a distinction between State Anxiety and Trait Anxiety [141], and also between State Anger and Trait Anger [142]. Upon his model, anxiety and anger can manifest themselves as personality traits, but also as emotions for shorter times. As such, State-Anxiety corresponds to an emotional state that "*consists of feelings of tension and apprehension and heightened autonomic nervous system activity*", and Trait-Anxiety corresponds to a personality trait that refers to "*individual differences in anxiety-proneness*" [141].

3.2 Cognitive States

The cognitive states which were the most studied in IVEs are cognitive load and mental workload. Those often designate the same concept in VR studies [121, 150], while not necessarily referring to the same one in the psychological field [57]. They can sometimes be considered as even or distinct, and can especially be confounded with their components or other concepts such as mental load, mental effort, performance, or cognitive workload [110].

Among popular definitions, Paas et al. [110] defined **cognitive load** as "*a multidimensional construct representing the load that performing a particular task imposes on the learner's cognitive system*" [111]. It has multiple aspects such as mental load, mental effort, and performance, and can be manipulated through the task and instructions presentation (see the Cognitive Load Theory [110]). On the other hand, **mental workload** is a subcomponent of workload, which can be defined as the sum of the demands a task imposes on an individual. Among the numerous proposed definitions, papers usually agree to determine mental workload as a multidimensional construct determined by characteristics of the task(s) (e.g., demands) and the operator (e.g., skills) [42, 61, 122]. For example, Wickens described mental workload as "*the relation between the (quantitative) demand for resources imposed by a task and the ability to supply those resources by the operator*" [153]. One theory is often associated with mental workload: Wickens [153]'s **multiple resources theory**. This theory proposes that human resources do not have only one information processing, but multiple resources which can be exploited simultaneously or sequentially depending on their type. It allows system designers to predict when certain tasks can be performed concurrently or will interfere with each other.

Cognitive load and mental workload are very close concepts that are tackled through different perspectives. Cognitive load particularly focuses on the interaction between the instructional design and the user's cognitive process architecture, and mental workload focuses more on the interaction between the nature of the task and the user's elicited pool of cognitive resources [153]. They are used in different contexts (i.e., respectively, mostly in the educational field and in ergonomics) and mainly relate to the user's ability to process task and information.

3.3 Presence and Affective and Cognitive States

VR technologies and IVEs were found to be efficient to induce and assess ACS, notably because they engage participants [124]. Users in VR are not just passive observers watching images on a screen, but active participants in a Virtual Environment (VE). From that aspect arises the sense of presence, an essential component of VR defined by Slater et al. as the sense of "*being there*", inside a virtual world [138]. It also has two other aspects: "*the extent to which the VE becomes the dominant one*", and "*the extent to which participants, after the VE experience, remember it as having visited a 'place' rather than just having seen images generated by a computer*" [137]. Indeed, presence in VR is important to evaluate the quality of immersion experienced by users, and it can be treated as a neuropsychological phenomenon [123]. It should, therefore, be taken into account as it can interfere and play a great role when studying other ACS.

The link between presence and ACS has been widely studied in previous research. Riva et al. found a circular interaction between presence and emotions [124]. On one side, the feeling of presence is greater in "emotional" environments, and on the other side, the emotional state is influenced by the level of presence.

Indeed, most studies agree to say presence is influenced by the intensity of emotions [5, 6, 14, 43, 60, 90, 124, 146] and cognitive load [83]. Emotional content [14, 15] and stories which are emotionally powerful and richly narrated [146] could contribute more to presence than technological factors (i.e., the degree of immersion [15, 146] and stereoscopy [14]). Furthermore, the nature of emotions could have an effect on presence [11, 105], even if some results do not support this statement [56]. Valence and arousal were found to have a positive relationship with presence [11, 105], and relaxation, a negative relationship with presence [105]. Some studies also found that presence is influenced by cognitive abilities [5, 43] and personality traits such as trait anxiety [5].

On the other hand, fewer results found an influence of presence on emotions. Studies usually agree to say this link exists but is more complex [14, 15, 55, 56, 60, 124]. For example, Gromer et al. found that presence due to the quality of the VE did not influence

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fear, but that presence due to individual variabilities predicted later fear responses [60]. As such, Felnhofer et al. suggested that presence was a precondition for emotions to be felt, but that it did not influence the intensity of emotions [55].

In summary, presence is an important factor widely studied in IVEs and was found to have a circular relationship with ACS. On the one hand, the intensity of emotions and cognitive load influences presence. On the other hand, the effect of presence on ACS is more complex. As such, it was suggested that presence was a precondition for emotions to be felt in IVEs.

4 Measuring Affective and Cognitive States in Virtual Reality

Various methods for measuring ACS have been proposed in the last decades. Thus, we will focus in this section only on the most widely used methods in IVEs. Kaplan et al. exposed three groups of strategies to measure emotions [66]: self-reports, observational methods, and psychophysiological measurements. Similarly, O'Donnell classified the methods to measure mental workload in three groups [104]: subjective (or self-reports), physiological, and task performance measures. We propose to merge their propositions as they have many common aspects by dividing the methods to measure ACS into four categories: self-reports, observational methods, task performances, and psychophysiological measures. Self-report methods are subjective as they collect the users' perceived and communicated experiences. On the other hand, observational, performance, and psychophysiological methods are objective as they can collect data at a high frequency without any intervention from the users. We will expose each four measurement categories, present the most widely used methods to assess ACS, and discuss their advantages and drawbacks in an IVE context.

4.1 Self-report Measures

Self-reports measures correspond to the methods in which individuals are asked to describe their ACS during a passed time period or at a given time. It usually involves the use of surveys or questionnaires, which can be paper-and-pencil, online or oral. It can also take other forms (i.e., interviews, self-confrontation).

4.1.1 Affective States

For the measure of **emotions from a dimensional perspective**, Bradley and Lang [31] developed the Self-Assessment Manikin (SAM), which depicts the three PAD dimensions of emotions by representing each of them by five graphic characters along a nine-point scale. This method was successfully used for the assessment of the user's emotion, especially the valence and the arousal dimensions. For the emotional valence dimension, the Positive and Negative Affect Schedule (PANAS) is a very popular method proposed by Watson et al. [152]. This method consists of two scales to measure positive affect and negative affect using ten psychometric items each.

Self-reports is also often used to measure **AS from a discrete perspective** by using Likert-Scales (LS), Visual Analogue Scales (VAS), and other custom questionnaires. Among standardized questionnaires, the State-Trait Anxiety Inventory (STAI) is a popular form often used to measure anxiety [142]. This test is composed of two scales of 20 propositions each: the STAI-S (state), also referred to as STAI form Y-A or Y1, and the STAI-T (trait), also referred to as STAI form Y-B or Y2. The STAI-T is usually used at the beginning of a protocol to recognize generally anxious people (who have higher scores). On the other side, the STAI-S score is a good indicator of short-term anxiety, and it can be used after each condition of a protocol. Spielberger et al. [142] also created a similar multi-scales for anger: the State-Trait Anger Expression Inventory (STAXI), which evaluates trait and state angers.

FIG. 2: Example of self-reporting method in an IVE. Instanteous Self-Assessment (ISA, measure of the user's mental workload using five different ratings [148]) in a VR Flight Simulator [87].

4.1.2 Mental Workload

To measure **mental workload**, Cain [33] divided the self-report methods into two categories: multidimensional and unidimensional scales. The most popular scales are **multidimensional** ones: the NASA-TLX [61], the Subjective Workload Assessment Technique (SWAT) [122], and the Workload Profile (WP) [151]. The NASA-TLX consists of six scales regarding workload: the mental demand, the physical demand, the temporal demand, the performance demand, the effort, and the frustration. Each of them is rated individually on a 0-100 scale, weighted, and aggregated for a global workload score. The SWAT considers the mental workload as composed of three components: the time load, the mental effort and the psychological stress load. It uses a method based on interval properties. Finally, the WP is based on the assumption that mental workload can be defined by the dimensions outlined in Wickens's multiple resources theory [153]. Among **unidimensional** scales, the Rating Scale of Mental Effort (RSME) [158] evaluates the mental effort on a continuous vertical axis from 0 to 150, and the Instantaneous Self Assessment (ISA) evaluates mental workload using five different ratings [148] (see Fig. 2). The latter has been especially used during flight training [148]. Unidimensional scales are quicker to respond but they can have a smaller diagnosticity as they consider only one dimension.

Self-report methods are considered as cheap and convenient. It is a well-accepted measure of ACS thanks to their self-referential nature and high face validity [66]. One of the main issues concerns the ability of individuals to reveal their ACS and their interpretation of the latter. Results are restricted by human language and can be biased depending on what individuals believed they felt, or on which ACS they wanted to report to be more socially desirable [84, 135]. Moreover, since real-time is an important aspect of VR, it is difficult to get a high-frequency measure of the ACS using self-reports. Depending on the way they are done, self-report measures can also break immersion in a VE [139] and have an impact on the user's subjective impression.

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4.2 Observational Measures

Unlike self-reports, observational methods are based on an exterior point of view and evaluation of body or facial behaviors. Those behaviors are usually associated with body language and include nonverbal indicators such as facial expressions, body postures (e.g., position of hands, style of walking), gestures, touch, and the use of personal space [129]. One can identify patterns of behavior, as well as their frequency of appearance and correlates them with ACS [102].

For the recognition of emotions, **facial expressions recognition** is from far the most popular observational method outside VR. Ekman et al. developed recognition methods for facial expressions of the Big Six emotions [51]: the FACS. It has proven to be a good standard for categorization and measurement of emotional expression but has some limitations in recognizing some expressions across different cultures due to facial deformations and skin colour [17, 64]. Moreover, it can be more challenging to do facial recognition in VR as parts of the face are most of the time occluded by the HMD. Multiple research paths were explored to try answering this problem using electromyography (EMG) [21, 95], photoreflective sensors [67, 147], proximity sensors [81], strain gauges to measure foam deformation on the HMD [80], and RGB-D camera on the mouth region [80, 106].

On the other hand, VR often implies body engagement, which makes **body gesture** recognition particularly interesting to study ACS. Noroozi et al. provided a survey on the emotional body gesture recognition, as well as a table with general movement protocols associated with the Big Six [102].

Other methods such as **voice treatment** have been less explored in VR but could be interesting given the growing interest in multi-user VR applications and their implication on oral interactions.

Interaction is one of the main components of VR [144], which makes users' behaviors particularly interesting to study in this context. In that sense, observational measures provide rich data and can be useful for examining ACS manifestation in real-time [66]. However, there are some limitations. This method can hardly be universal. ACS such as emotions are built over a lifetime, and their manifestation can vary across different individuals depending on factors such as their cultures, personalities, and genders [17, 94]. Also, people can intentionally express, suppress or hide their psychological states during an observation. Their behaviors can be modulated by the environment (e.g., real or virtual) and the situation (e.g., experimental or entertainment). Moreover, VR equipment can be cumbersome and sometimes make the behavior in IVEs less natural. It is also worthwhile noting that most observational measures greatly depend on the context and interactions users have to perform in the application.

4.3 Tasks Performance Measures

Task performance measures have mainly been explored in works studying CS. O'Donnell distinguished two major types of performance-based measures [104]: primary task measures and secondary task measures. Primary task measures attempt to directly assess the user's performance on the task of interest. Typical measures of task performances include accuracy, reaction or response times, and error rates. They can be insensitive to the user's CS if the variability in task demands are insufficient to result in observable changes as they do not give information on the user's remaining cognitive capacities. On the contrary, secondary task measures provide an index of the remaining operator capacity while performing the primary tasks. There are two methodologies for secondary tasks: auxiliary task and loading task [33]. In auxiliary task methods, users are instructed to maintain consistent performances on the primary task regardless of the difficulty of the overall task. Therefore, the secondary task performances are an indirect indicator of the user's reserve capacity. In the loading task approach, the secondary task deliberately causes degradation of the primary task, which require consistent performances on the secondary task. The primary task performance measures are, in that case, more sensitive to the users' mental workload variations.

Task performance measures have great advantages as they can be assessed easily and continuously. However, similarly to observational measures, they are context-dependent. They were shown to have great correlations with CS but can be modulated by the users' engagements which can make them inaccurate for the measure of ACS [48, 104, 151].

4.4 Psychophysiological Measures

The term psychophysiology refers to the physiological responding to psychological phenomenons. In physiological computing [53], physiological activities and changes are direct reflections of processes in the Autonomic Nervous System (ANS) and in the Central Nervous System (CNS). Since physiological responses are issued from psychological processes, it was hypothesized that it is possible to translate them to psychological states via the extraction of some specific features [118].

4.4.1 Measure of the ANS

The most frequently used physiological measures of ACS are indicators of the ANS. Those are uncontrolled consequences of the CNS activity on physical processes. Kreibig provided a review of the ANS activity, detailing the physiological signal feature reliability and behaviour depending on the different elicited emotions [76]. Although there are still debates about the relation between ANS measures and psychological activities [94], the use of these measures to assess negative arousal is uncontested [66]. The most popular measures of the ANS activity include cardiovascular, electrodermal, and pupillometry indicators.

Cardiovascular activity can be measured by means of electrocardiography (ECG), and photoplethysmography (PPG). On the one hand, **ECG** detects electrical changes that originate from the ventricles contracting and expelling blood. On the other hand, **PPG** uses a small optical sensor in conjunction with a light source to measure changes in the skin light absorption as blood perfuses through the skin after each heartbeat. PPG sensors usually are less obtrusive, but also less accurate than ECG methods. Among the popular features, both sensors can be used to extract the Heart Rate (HR) and the Heart Rate Variability (HRV), which corresponds to the adaptation changes in the time intervals between two consecutive heartbeats in response to an environmental and/or an internal stimuli [97]. For instance, anxiety is usually associated with an increase in HR and a decrease in HRV [76]. On the other hand, **electrodermal activity** (EDA), often referred to as Galvanic Skin Response (GSR), is the term used to define autonomic changes in the electrical properties of the skin [136]. The activity of the sympathetic nervous system is directly linked to the activity of the sweat glands, which is in turn related to the activity of the skin epidermis [28]. The EDA can be represented by its two main components: the tonic skin conductance and the

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phasic skin conductance. The tonic skin conductance corresponds to the normal conductance of an individual in the absence of any stimulus of discrete changes in the experimental environment and is related to the Skin Conductance Level (SCL). The phasic skin conductance happens in accordance to an affective event [85] and is related to the Skin Conductance Responses (SCR). The EDA has proven strong content validity and is widely used to measure a user's affective and cognitive changes [53]. For instance, fear was reliably associated with an increase in SCR and SCL responses [76]. As for **pupillometry measures**, they can be assessed using eye-tracking devices. Changes in pupil size are caused by two antagonistic muscles: the dilator pupillae, which dilates the pupil, and the sphincter pupillae, which constricts it [50]. The pupil dilation is provoked by activity in the sympathetic pathway of the ANS (fight-or-flight), and the constriction by activity in the parasympathetic division of the ANS (rest-and-digest) [50]. Pupil dilation data was especially shown to be influenced by cognitive efforts [40, 50]. Derived behavioural measures such as gaze direction, blinks, fixation, and eyes saccades were also largely exploited in the analysis of the human's ACS in the literature [34, 37, 40]. Aside from these measures, **respiration** (Resp), **skin temperature** (Temp), **electrooculography** (EOG) and EMG measures can also be affected by the ANS processes linked to a change in the user's ACS [85].

There are good practices that suggest placing ANS sensors at specific places [157]. In VR studies, ECG electrodes usually are placed on the user's torso (e.g., via a belt), PPG sensors on the earlobes or the wrist, and EDA sensors, on the fingers, wrist, or directly on the face using the headset. Eye-trackers are also more and more directly built in VR HMDs. To take into account within and between-individual variability, most studies use a baseline to observe changes or to normalize the obtained signals.

4.4.2 Measure of the CNS

Electroencephalography (EEG) and other neuroimaging methods measure directly the activity caused by the functioning of the CNS. The frontal lobe of the cortex, which is the largest part of the human brain, is notably responsible for conscious thought, which makes it the most impacted by the ACS [3].

EEG measures rhythmic macroscopic neural oscillations produced by the synchronized activity of brain neurons by placing electrodes on the scalp and amplifying the signals. These oscillations can notably be observed in specific frequency ranges named as α (8-13 Hz), δ (1-4 Hz), θ (4-8Hz), β (13-30 Hz) and γ (30-70 Hz) frequency bands. Specifically, θ, α, and β waves have been found to be impacted by cognitive performances and the mental effort [54]. Another popular and affordable neuroimaging methods is the functional Near-Infrared Spectroscopy (**fNIRS**), a multi-wavelength optical spectroscopy technique that measures hemodynamic brain responses resulting from intentional sensory, motor, or cognitive activities [9]. Similarly to PPG sensors, fNIRS systems use skin tissue's particular absorption properties in the near-infrared range to measure and localize changes in oxygenated (i.e., HbO2) and deoxygenated (i.e., HbR) hemoglobin concentration following neural activation. Overall, increasing task difficulty was found to increase HbO2 and decrease HbR [134]. Studies using both systems corroborate the fact that positive and negative affects are respectively associated with the frontal left and right hemisphere of the brain [3]. EEG is known to have a high temporal resolution but a low spatial resolution on the brain [41]. Compared to EEG, fNIRS offers a less accurate temporal assessment of the brain activity but a better spatial resolution and is less sensitive to movements. Other neuroimaging methods such as magnetoencephalography and functional Magnetic Resonance Imaging offer a more precise assessment of brain activity location and a good temporal resolution. They have been used with VR devices [35]. However, they can hardly be used outside a clinical context as they are not mobile.

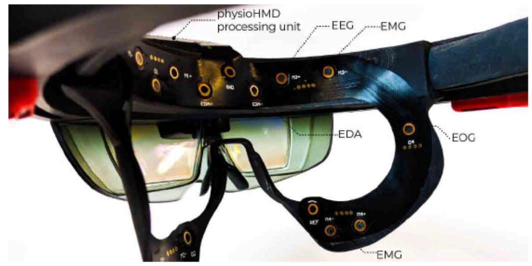

FIG. 3: Example of module which integrates physiological sensors directly on the headset. PhysioHMD [21].

Measures of the CNS can provide reliable estimations of the emotions [3, 133], but also of the cognitive load [7] or mental workload [10]. However, they can be cumbersome, sensitive to motions and thus, complex to use with VR headsets.

Overall, psychophysiological measures have been widely studied in and outside VR. The measures of the ANS and CNS are both interesting since they provide high frequency and objective measures of the physiological activity influenced by the user's psychological state. It is one of the most considered solutions to measure ACS from an objective perspective in VR (see Tab. 1). One downside is that the sensors can be cumbersome, thus reduce immersion in VEs. For that reason, many laboratories and companies have focused on integrating physiological sensors directly on VR headsets in recent years. For example, PhysioHMD introduces EEG, EMG, EOG, and EDA directly on the headset (see Fig. 3) [21], EmotionalBeasts study introduced EDA and PPG on the HMD [20], and LooxidVR[1] and Neurable[2], EEG on the HMD. Still, one matter of concerns is that physiological sensors are often sensitive to movements, which makes interactions and locomotion in VR sources of artefacts in the signals. Additionally, they can be difficult to interpret [53] and can greatly be influenced by within and between-individual variabilities [149] and cybersickness [44, 69].

5 AFFECTIVE AND COGNITIVE VIRTUAL REALITY

This section provides an overview of research in Affective and Cognitive VR in IVEs in a non-clinical context. Combining ACS and VR has advantages in several application fields. Among the 63 studies retained in this survey, most focused on **global VR** applications to understand how users felt in a VR context and how to enhance VR application using the user's mental state (i.e., 37 studies) [5, 11, 13, 14, 15, 16, 19, 20, 29, 32, 34, 36, 37, 46, 47, 48, 49, 55, 56, 58, 60, 74, 79, 83, 86, 88, 89, 90, 91, 98, 105, 108, 113, 117, 124, 140, 143]. 10 focused on **artificial intelligence** (AI) applications by training ACS recognition models in VR [2, 21, 24, 92, 93, 96, 100, 121, 126, 150]. Five were done in a **gaming** context [1, 62, 82, 109, 112], three in a **military**

1. Looxidvr. https://looxidlabs.com/looxidvr/. Accessed: 2020-03-02.
2. Neurable. https://neurable.com/. Accessed: 2021-03-17

context [114, 115, 154], two in a **sport** context [8, 145], two were applied in an **educational** context [39, 43], two were done to improve immersive **training** [38, 87], one targeted an **aerospace** application [6], and one focused on the benefits of immersion for **journalism** [146]. The measured ACS in the 63 studies are summarized in Fig. 4.

FIG. 4: Illustration of the relative occurrence of the different measured ACS in the 63 Affective and Cognitive VR studies retained in this survey. Light blue corresponds to emotions from a dimensional perspectives. Dark blue corresponds to discrete AS. Green corresponds to measures linked to CS. The most measured ACS were Arousal and Valence with 16 occurrences each.

We decided to treat the 63 studies following the three categories: induction, recognition, and exploitation of ACS (Fig. 1). The first group of studies explored methods to **induce ACS**, as well as the influence of specific IVEs parameters on users' ACS (see Tab. 1). The second group deals with studies which developed models to **recognize ACS** using physiological signals and ML algorithms in IVEs (see Tab. 3). Finally, the last identified group targets **the exploitation of ACS** to modulate IVEs content and parameters based on ACS measures (see Tab. 2). Some studies were therefore classified in several of these categories.

5.1 Induction of Affective and Cognitive States in VR

This section aims to depict the results of studies that found an influence of IVEs variables on the user's AS or CS. Therefore, stimuli used to elicit ACS or which have shown to influence ACS are detailed in Table. 1, as well as the methods used to measure ACS. The studies can be divided into two sections depending on their purposes in regards to the induction of AC or CS: studies that aim to induce a variety of different ACS or different levels of ACS, and studies whose objectives are to study the influence of specific parameters on an AS or a CS.

5.1.1 Induction of Several Affective and Cognitive States

Studies that intended to induce different ACS or different levels of ACS have mainly used emotional videos, emotional VEs, emotional scenarios, or cognitive tasks in IVEs.

Emotional videos designate panoramic 360°videos displayed in a VR device. There is no 3D object nor interaction and users can only navigate in a limited space and/or move their head. As such, Li et al. developed a library of 73 immersive VR clips which were labelled using arousal and valence responses [79]. This was done similarly to previous works which developed databases of affective stimuli based on pictures (e.g., the International Affective Picture System (IAPS) [77]) or audio sources (e.g., the International Affective Digital Sounds (IADS) [30]) in VR. In another study, Mavridou et al. presented 20 non-panoramic emotional videos from an affective film library [130] along with 20 neutral videos in a VR cinema environment. The 20 emotional videos managed to induce balanced classes of emotions (i.e., 2 levels of arousal $\times$ 2 levels of valence, five videos per classes). In the same line, Marín-Morales et al. presented four architectural 360° panorama environments which succeeded to elicit 2 levels of arousal $\times$ 2 levels of valence by varying colours and geometries [92] (see Fig. 5). On the other hand, Macedonio et al. presented 10 anger-provoking scenes via panoramic videos to users [88]. Those managed to induce anger responses to users (see Table. 1). In the journalism field, Sundar et al. presented two stories in a VR HMD: a sad one about refugees, and a more positive one about dolphins [146]. Those induced the expected valence response. It is also the case for Anderson et al.'s study, which presented a neutral 360° classroom class scene, and two natural panoramic views that reduced negative affects [6].

As for **emotional VEs**, those imply 3D objects but no other interactions than navigating in the VE and moving the head. The Empathic Computing Lab developed five VEs based on a jungle safari to induce happiness, anxiety, fear, disgust, and sadness [36, 37, 47]. Users are on a car that moves through the safari, and they are exposed to audio-visual stimuli. A pilot study was conducted to make sure the environments triggered the appropriate emotions [36, 47]. In the EMMA Project [4], a procedure was developed to induce different moods/emotions using a virtual park scene. The user explores a park, in which light and other audio-visual stimuli change depending on the targeted mood. The park was shown to induce sadness, joy, anxiety, relaxation, and neutral states [14, 15, 16, 124]. In the same line, Felnhofer et al. developed five virtual parks which induced joy, sadness (no effect), boredom, anger, and anxiety by varying weather, sounds, light, and animated contents [56]. Robitaille and McGuffin also developed a virtual forest that could change from a calm to a stressful condition by varying similar parameters [126]. Other studies made use of distinct VEs to elicit different emotions [34, 82, 105]. On the stressful and anxiety side, a famous study in VR consists of the virtual pit, which exposes a user to a fear of height situation [98]. It successfully increased presence and induced changes in the users' psychophysiological responses [60, 90, 98].

Furthermore, **emotional scenarios** are emotional VEs in which users can interact with virtual entities. Those can be horror games [46, 62, 112], games that are supposed to elicit sadness [109], joy [24, 46], neutral games [11], or serious games [38, 43, 87]. VR games and scenarios are usually very engaging and were shown to influence emotions [38, 43, 46, 62, 109, 112], CS [38, 43, 87], and flow [24]. Moreover, one large field of interest in VR concerns virtual public speaking situations [55, 74, 83, 117, 140]. Those were found to greatly influence anxiety, which can also be modulated by the virtual audience type [117, 140] and its reaction [74]. More specifically, some studies focused on the effect of threatening [114, 154] or emergency situations [2] on physiological signals and cognitive tasks performance. Others used everyday anxiety-provoking situations (e.g., a test day [5]) and VR sport to validate anxiety stimuli such as the crowd and the presence and reaction of characters in a competitive situation [8, 145].

On the other hand, works studying CS are using most of the time **cognitive tasks**. As such, the n-back task is a standardized cognitive task targeting working memory which can be declined in different difficulty levels and has been used extensively in VR to

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FIG. 5: Induction of two levels of arousal and two levels of valence using four architectural 360° panorama environments in a VR HMD [92]. Left: negative valence; right: positive valence; bottom: low arousal; top: high arousal.

induce different levels of mental workload. It can be auditory [86] or visual, and the stimuli can take different forms such as color balls [121, 150], letters (for verbal task) or oriented symbols (for spatial task) [32]. Steed et al. also used a letter recall task, which targets users' working memory, to test the influence of some independent variables on cognitive task performance [113, 143]. On the other hand, Bergström et al. used a counting backward task [19], which targets executive functioning. Similarly, Banakou et al. used a post-experiment Tower of London task [13], which especially targets planning and problem-solving skills. On the mental rotation side, Collins et al. [39] used a spatial rotation task to induce different levels of cognitive load. Spatial rotation tasks were also used as distractors in [113, 143]. Dey et al. [48] and Gerry et al. [58] made use of a visual searching task, where users had to find a target shape among several colored visual distractors, to generate different task load levels. Recall of objects questionnaires are also often used to assess spatial awareness in VEs [49, 89, 91]. Cognitive tasks can also be used to induce arousal, such as arithmetic tasks (e.g., [6]), or the Virtual Reality Stroop Task used in [114, 154], adapted from the paper and pencil Stroop Test. These tasks were used as single standardized tasks to induce different levels of CS using different difficulty levels, but some studies also explored multitasking in IVEs to modulate the user's mental workload or arousal level [87, 114].

5.1.2 Other Factors Influencing Affective and Cognitive States

Factors such as the type of display, the immersion levels, avatars, and users' profiles were found to impact users' ACS.

The relation between the **the type of display, the immersion levels** and users' ACS can be complex as some studies found an effect of IVEs on ACS [89, 93, 112], and others did not [74, 86]. For example, Pallavicini et al. found no effect of VR vs non-immersive console on anxiety. However, they found that VR provoked more happiness than non-IVEs [112]. These results go in the same line as other studies' findings [89, 93]. A supposition is that the novelty of VR could elicit this difference in emotional responses [93, 112]. Moreover, immersive display can induce more intense AS [38, 146], improve spatial awareness [89], and learning retention [38] compared to non-immersive methods and display. Furthermore, simulation fidelity was found to increase sport anxiety [145] and memory of objects [91]. On the other hand, stereoscopy did not show an influence on emotions [14, 83].

Avatars were also found to influence ACS. For example, Osimo et al. proposed a self-therapy where the user is describing a problem and answering to themselves by embodying first the patient, and then the counsellor body [108]. The experiment, and the body ownership illusion were found to improve mood and emotions, especially when the user was embodied in Freud's body as the counsellor. Furthermore, embodying a virtual body associated with high cognitive abilities such as Einstein was found to result in better cognitive performance and in a decrease of age-based discrimination in [13]. Self-avatar with hand gestures allowance [143], as well as avatar types (full-body, real-body, hands-only, no body) [113] were also found to have significant effects on cognitive task performances. These results suggested that a higher sense of embodiment was associated with greater cognitive task performances. In the same line, being embodied in an uncomfortable posture resulted in changes in the physiological signals and in more mistakes in a cognitive task [19]. Bourdin et al. also discovered that a virtual out of body experience resulted in a lower fear of death [29].

Aside from avatars, **personality traits** such as trait anxiety can influence emotions [5, 55, 117]. Users who are originally anxious will experience greater anxiety and discomfort in anxiety-triggering IVEs [5, 55]. **Other paradigms** like redirected walking were also found to increase cognitive task performances and impact walking behaviour [32]. On the interactions side, body participation and voice control improved emotions and enjoyment compared to more classical interactions [11, 109]. In another study, Dinh et al. found that multi-sensory feedback such as tactile, olfactory and auditory ones resulted in a greater memory for objects in the VEs [49]. In the same line, Chen et al. discovered HR feedback in emotional VEs to be more enjoyable than no HR feedback, especially audio-haptic HR feedback [36]. They also found that altering the HR feedback could change participants' emotions but not their physiological signals themselves [47]. However, there was no effect of sharing HR to another player in collaborative games on the observer's emotion and empathy [46]. In a horror game, Houzangbe et al. found that users who tried to influence their HR (biofeedback to control fear stimuli and stressors) experienced more fear than those who did not [62].

In conclusion, studies that intended to induce different AS or different levels of AS mainly used emotional videos, VEs, and scenarios. As for the induction of CS, studies mainly adapted standardized cognitive tasks in VR. Cognitive tasks were also found to increase the user's arousal level. Furthermore, immersion, high-fidelity displays, and multi-sensory feedbacks were found to increase AS intensity, improve AS and cognitive performances. Altering the avatar's control and appearance, and redirected walking was also found to increase cognitive demands. Also, embodiment in VR can enhance the user's cognitive experience and performance. Finally, personality traits and physiological feedback can also influence the user's ACS.

5.2 Recognition of Affective and Cognitive States in VR

Recent studies tried to passively measure users' ACS in IVEs by developing recognition models. Such models have the advantage to assess the users' psychological states without having to disrupt their immersion in the VE. However, recognition models typically require the use of objective measures to be continuous. In IVEs, studies mainly relied on physiological signals (see Tab. 3). Due to the complexity of physiological data, Machine Learning (ML)

TABLE 1: Summary of works that induced ACS in IVEs. Significant changes are indicated in bold in "Objective Measures" and "Subjective Measures" columns. Significant effects are indicated in bold in the "Inducer" column. In the "Inducer" column, the emotional VEs, videos, and games are not detailed when several of them are used in the study.

Ref.	ACS	Measured ACS	Subjects	Field	Inducer	Objective Measures	Subjective Measures
[105]	AS	Arousal, Valence, Dominance	146	VR	**Emotional VEs, presence**	-	**SAM**
[37]	AS	Arousal, Valence, Dominance	20	VR	**Emotional VEs, HR sensory feedback**	**Behaviour, Pupil Dilatation**	PANAS, SAM
[47]	AS	Arousal, Valence, Dominance	19	VR	**Emotional VEs, HR feedback frequency**	HR (ECG), EDA	**PANAS**, SAM
[79]	AS	Arousal, Valence	95	VR	**Emotional videos**	**Behaviour**	**SAM** (2D)
[96]	AS	Arousal, Valence	11	AI	**Emotional videos**	**HR** (PPG and ECG)	**Continuous Affect Self-Rating**
[92]	AS	Arousal, Valence	38	AI	**Emotional VEs**	**HR** (ECG), **EEG**	**SAM** (2D)
[93]	AS	Arousal, Valence	60	AI	**Emotional VEs, baseline with IAPS and emotional VEs**	**HR** (ECG), **EEG**	**SAM** (2D)
[11]	AS	Arousal, Valence	56	VR	**Presence**, body participation in a pick and place game	-	**SAM** (2D)
[146]	AS	Arousal, Valence, enjoyment	129	Journalism	**Emotional videos, Emotional VEs**	-	**Valence and emotional intensity scales, Empathy adjective scale**
[108]	AS	Arousal, Valence, "global Mood"	22	VR	**VR self-therapy, Avatar type** (Freud vs look-alike), **Avatar control** (synchrone, asynchrone)	-	**Profile Of Mood States, SAM** (2D), **SUDS**
[126]	AS	Arousal	12	AI	**Stressful situation**	**Behaviour, HR** (ECG), EDA,	**SAM**
[88]	AS	Arousal, Anger	41	VR	**Emotional videos**	**HR** (ECG and PPG), EDA, **Resp**, Temp	**STAXI-2, PANAS, VAS** (arousal), **LS** (10 points, Anger)
[46]	AS	Valence	26	VR	**Emotional games, HR of a collaborator feedback**	**Eye Behaviour**	**PANAS, Inclusion of Other in Self scale**
[16]	AS	Valence, Anxiety, Joy, Sadness	110	VR	**Emotional VEs**	-	**LS** (7 points - Sadness, joy, anxiety, relaxation), **PANAS**
[124]	AS	Valence, Anxiety, Anger, Disgust, Happiness, Sadness, Surprise	61	VR	**Emotional VEs, presence**	-	**LS** (10 points - Sad, Happy, Anxious, Relaxed), **VAS** (Happiness, Sadness, Anger, Surprise, Disgust, Anxiety, and Quietness), **PANAS, STAI-S**
[145]	AS	Anxiety	25	Sport	**Anxiety triggers, field of regard, simulation fidelity, trait-anxiety, sport experience**	Task perf., Behaviour, HR (ECG), **EDA**	**State-Trait anxiety Inventory of Cognitive and Somatic Anxiety** (state), **Competitive state anxiety inventory-2**
[5]	AS	Anxiety	210	VR	**Anxiety triggering situation, trait anxiety, personality, individual spatial abilities**, computer experience	-	**STAI-S, SUDS**
[8]	AS	Anxiety (Social Anxiety)	18	Sport	**Sport competition scenario**	Task perf., **Behaviour**, HR (ECG), EDA	**LS** (7 points - on mental state, motivation, perception of the VE during the competition)
[56]	AS	Anxiety, Boredom, Joy, Sadness	120	VR	**Emotional VEs**, presence	EDA	**modified DES** (Differential Emotions Scales)
[60]	AS	Anxiety, Discomfort	49	VR	Realism, presence, **fear of height situation**	**HR** (ECG), **EDA**	**Acrophobia Questionnaire, STAI-S, SUDS**
[83]	AS	Public Speaking Anxiety	86	VR	Stereoscopy, **presence, virtual public speaking situation**	**HR** (PPG)	**MPRCS**
[74]	AS	Public Speaking Anxiety/Fear (stress physiological response)	66	Therapy	Virtual/real, **public speaking situation**	**HR** (ECG), **Salivary Cortisol**	PRCS (Personal Report of Confidence as a Speaker), **STAI-S**
[117]	AS	Public Speaking Anxiety/Fear	40	VR	**Virtual public speaking audience types, prior public-speaking anxiety, immersion**	-	**MPRCS** (Modified Personal Report of Confidence as a Speaker), **somatic response, self-rating of talk perf.**
[140]	AS	Public Speaking Anxiety/Fear	41	VR/Therapy	**Public speaking phobic participants, virtual public speaking situation**	**HR** (ECG)	**MPRCS, APQ**
[90]	AS	Anxiety, Fear of Height (via HR and Discomfort)	41	VR	**Threatening situations (predicted or not)**	**HR** (ECG)	**SUD** (Subjective Units of Discomfort)
[34]	AS	Anxiety, Happiness, Sadness, (Physiological signals)	20	VR	**Emotional VEs, cybersickness inducer**	**HR** (PPG), **Eye-tracking data**	**LS** (7 points - happy, sad, comfortable, anxious)
[14]	AS	Anxiety, Joy, Sadness, Valence	40	VR	**Emotional VEs**, stereoscopy	-	**LS** (10 points - Sadness, joy, anxiety, relaxation), **PANAS**
[112]	AS	Anxiety, Happiness, Surprise	26	Gaming	**Horror game, immersion**, trait anxiety	**HR** (ECG), **EDA**	VAS (**Anxiety, Happiness**, Surprise)

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Ref.	ACS	Measured ACS	Subjects	Field	Inducer	Objective Measures	Subjective Measures
[55]	AS	Anxiety (social)	65	VR	Presence, **social anxiety, virtual public speaking situation**	**HR** (ECG)	**STAI-S**
[109]	AS	Enjoyment, Sadness	22	Gaming	**Sad game, voice control interaction**	-	**LS** (7 points - enjoyment, emotionally affected by the game)
[98]	AS	Fear of Height (via physiological signals)	259	VR	**Fear of height situation, multiple exposures, passive haptics, frame rate, latency**	**HR** (PPG and ECG), **EDA, Temp**	-
[29]	AS	Fear of Death	32	VR	**Out of body experience types, visuotactile and visuomotor synchrony**	-	**Collett-Lester Fear of Death scale**
[62]	AS	Fear	32	Gaming	**Horror game, HR biofeedback**	**Task perf., HR**	**LS** (5 points - fear (in engagement items))
[2]	AS	Excitement trend	20	AI	**Emergency situation**	**EEG, Eye Behaviour**	-
[24]	AS	Flow	36	AI	**Shooting game**	**HR** (ECG), **Resp**, EMG	**Flow Short Scale**
[82]	AS	(Physiological signals)	26	VR	**Emotional VEs**	**EDA, HR** (ECG)	-
[36]	AS	(Physiological signals)	7	VR	**Emotional VEs, multi-sensory HR feedback**	**Eye-tracker data**	-
[15]	AS	Emotional Engagement	60	VR	**Emotional VEs, immersion**	-	**LS** (10 points - emotional engagement and indifference)
[6]	ACS	Arousal (physiological), Valence	18	Aerospace, medicine	**Emotional VEs, VE preference, cognitive task**	HR (ECG), **EDA**	**PANAS**
[114]	ACS	Arousal (physiological)	50	Military	**Threat situation levels, cognitive task presence**	**HR** (ECG), **EDA, Resp**	(Cognitive workload levels = cognitive task levels)
[154]	ACS	Arousal (physiological), Cognitive perf.	18	Military and AI	**Threat situation levels, cognitive task levels**	Task perf., **Behaviour, HR** (ECG), **EDA, EEG, Resp**, EOG	-
[38]	ACS	Arousal (physiological), Fear	48	Transport	**Aviation safety education method** (card vs VR), **aviation emergency scenario**	**Task perf.** (knowledge retention), **EDA, HR** (PPG)	**LS** (7 points, 6 fear-related adjectives, 6 engagement-related statements)
[43]	ACS	Positive and Negative emotions	23	Learning	(Positive emotions, cognitive abilities, immersions) on presence, **educational VEs**	-	**LS** (6 points, positive emotions: enjoyment, hope, pride and positive deactivating emotion : relief)
[89]	ACS	Enjoyment, Fear, Cognitive Perf.	63	VR cinema	**Emotional videos, display types**	**Tasks perf.** (among which, **spatial awareness**)	LS (5 points - **enjoyment** ; fear, nervousness), Narrative Engagement Questionnaire
[87]	CS	Mental Workload	53	Training	**Piloting, communication, resources management tasks**	**Tasks perf.**	**ISA**
[39]	CS	Cognitive Load	24	Learning	**Spatial rotation task** (3 levels) for classification	Task perf., **HR** (PPG), **EDA**, Temp, and Accelerometer (filter)	Self-reported moments of insight, (Cognitive workload levels = cognitive task levels)
[48]	CS	Cognitive Load	14	VR	**Visual search task** (20 levels)	Task perf., **EEG**	-
[86]	CS	Mental Effort	27	VR	**N-back task** (1, 2, 3), **walking**	**Task perf., Behaviour, HR** (PPG), EDA	**RSME**
[121]	CS	Mental Workload	10	AI	**N-back task** (1, 2, 3)	**fNIRS**	(Mental workload levels = cognitive task levels)
[150]	CS	Cognitive Workload	15	AI	**N-back task** (0, 1, 2)	**EEG**	(Cognitive workload levels = cognitive task levels)
[13]	CS	Cognitive Perf.	30	VR	**Virtual body** (Einstein vs young male)	**Task perf.**	**Implicit Association Test**
[19]	CS	Cognitive Perf.	31	VR	**Comfortable or not virtual body posture, body ownership illusion, cognitive task**	**Task perf., HR** (ECG)	**Autonomic Perception Questionnaire**
[32]	CS	Cognitive Perf.	16	VR	**Cognitive task** (verbal vs spatial vs none), **redirected walking curvature gains**	**Tasks perf., Behaviour**	-
[113]	CS	Letter Recall Task perf.	32	VR	**Avatar types** (no body, hands-only representation, articulated body and real)	**Task perf., Behaviour**	-
[143]	CS	Letter Recall Task perf.	40	VR	**Self-avatar presence, hands gestures allowed or not**	**Tasks perf., Behaviour**	-
[91]	CS	Object Location Memory	30	VR	**Rendering quality**	**Task perf.**	-
[49]	CS	Object Location Memory	322	VR	**Multi-sensory modalities** (tactile, olfactory, auditory), visual details	**Task perf.**	-

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TABLE 2: Summary of works that exploited ACS in IVEs. **Explicit** refers to an adaptation of the IVE knowingly to users, and **Implicit** refers to an adaptation of the IVE unknowingly to users. "Explicit exploitation" has two subcategories: **BF**: Biofeedback, which refers to studies that incite users to control their physiological state through feedback in the IVE; and **PF**: Physiological Feedback, which refers to studies that directly display the users' physiological signals features in the virtual environment or to a third party interface.

Ref.	ACS	Exploitation	Field	Targeted ACS	Feedback	Feedback Ref.	Feedback Triggering Event	Exp. validation
[48] [58]	CS	Implicit	VR	Cognitive Load	Visual search task difficulty (10 levels)	EEG	Threshold (based on EEG during baseline)	yes
[115]	ACS	Implicit	Military	Arousal (physiological), Cognitive Workload	Following a vehicle while driving in threatening situations: Audio-visual-olfative stressors for arousal, task difficulty for cognitive workload	ECG, EDA & EOG	Thresholds (based on a normative database)	no
[1]	AS	Implicit	Gaming	Excitement, Frustration	Obstacle game difficulty (2 levels)	EEG	EEG excitement and frustration indexes	yes
[20] [21]	AS	Implicit	AI	Anger, Stress, Neutral, Happiness (2 valence x 2 arousal)	Avatar appearance: Fur (2 happiness levels), particles brightness (2 stress levels) and colour (2 anger levels)	EDA, HR (PPG)	Emotion recognition	no
[21]	AS	Implicit	AI	Fear	360° horror video: Scene occlusion following user's gaze direction	EDA	Real-time	no
[21]	AS	Explicit	Therapy	Fear	Insects spawn rate, speed, behaviour and size (3 arousal levels)	EDA	Thresholds (manually set for each participant)	no
[62]	AS	Explicit - BF	Gaming	Fear	Horror game difficulty (5 levels) via audio-visual fearful stimuli & field of view reduction	HR (PPG)	Thresholds (compared to HR during baseline)	yes
[100]	AS	Explicit - BF	Gaming	(Physiological Regulation)	Rescuing a cat game: Auditory indicators of cat's location	HR (PPG)	Threshold (at 95% of the mean HR during baseline)	no
[47]	AS	Explicit - PF	VR	Valence, Arousal, Dominance	Altered audio-haptic HR feedback	HR (PPG)	Real-time	yes
[36]	AS	Explicit - PF	VR	Valence, Arousal, Dominance	Multi-sensory HR feedback modalities	HR (PPG)	Real-time	yes
[46]	AS	Explicit - PF	VR	Valence	Visual feedback of another user's HR in a collaborative game	HR (PPG)	Real-time	yes

TABLE 3: Summary of works that recognized ACS in IVEs.

Ref.	ACS	Classification of:	Input	Algorithm	Subjects	Labeled Data	Model Evaluation	Accuracy
[96]	AS	2 arousal levels	PPG; ECG	SVM	11	10560	Bradley's test	-
[154]	AS	3 arousal levels	EDA, RESP, EEG, ECG	SVM	18	2700	5-fold cross-validation	96.90%
							leave-1 out participant	36.90%
[92]	AS	2 arousal levels	EEG, ECG	SVM	38	152	leave-5 out participants	75%
		2 valence levels	EEG, ECG	SVM	38	152	leave-5 out participants	71.21%
[93]	AS	2 arousal levels	EEG, ECG	SVM	< 30	-	leave-1 out participant	75%
		2 valence levels	EEG, ECG	SVM	< 30	-	leave-1 out participant	71.08%
[2]	AS	2 excitement trends	Eye movement	Deep neural network (best)	20	220	Train(70%) / Test(30%) Split	92%
[150]	CS	3 cognitive load levels (task levels)	EEG	Regularized LDA	15	3420	4-fold cross-validation	63.90%
[121]	CS	3 cognitive load levels (task levels)	fNIRS	Shrinkage LDA	10	220	10-fold cross-validation	42%
[39]	CS	3 cognitive load levels (task levels)	EDA	Random Forest (best one)	24	345	10-fold cross-validation	50.83%
		3 cognitive load levels	HR	Random Forest	24	345	10-fold cross-validation	91.71%
		2 moments of insight	EDA	Random Forest	13	43	10-fold cross-validation	83.65%

methods are usually required in order to extract the users' ACS. These algorithms aim to infer the function between the input (e.g., physiological data) and the output data (e.g., the subjective AS or CS measure) using supervised techniques [75]. A challenge remains the training of ML models as they require the gathering of labeled data and specific induction protocols to ensure that different classes of ACS are generated. A summary of the different works which developed an ACS recognition model in an IVE is given in Table 3.

5.2.1 Classifiers

There is no consensus over which **ML algorithm** to use depending on the targeted AS or CS and the used sensors. Support Vector Machines (SVM) and Linear Regression Analysis (LDA) are popular methods that have been used for years in the ML community. However, the random forest algorithm also has shown great results in recent years [2, 39, 52]. For example, Collins et al. used Principal Component Analysis (PCA) and SVM with linear basis function, MultiLayer Perception, K-nearest neighbours (k=1), J48 Decision Tree, and random forest (100 trees) to classify three cognitive load levels and two moments of insight [39]. They found random forest to perform the best among the different classifiers. As for the models evaluation, it should be noted that most studies used a user-dependent approach (by using k-fold cross-validation, or leave-n out participant after having pooled all participants data together), meaning that these models require to be trained using the user's data to reach similar classification performances.

ML models training require to **label** the dataset for the classification of the user's AS or CS. As such, Mavridou et al. [95] and Marín-Morales et al. [92, 93] used self-report measures to label their physiological dataset. However, the user's psychological state was sometimes inferred in other studies. For example, Abdessalem et al. extracted the excitement trend (increase or decrease) based on the excitement index given by the Emotiv EEG device, which algorithm is currently not public [2]. In CS studies, task difficulty levels were often used to label the physiological dataset to recognize cognitive load and mental workload. As such, Tremmel et al. and Putze et al. both used the difficulty levels of the n-back task to label their dataset [121, 150]. Similarly, Collins et al. extracted three difficulty levels of a spatial rotation task based on the users' overall performances. Using another approach, the users' arousal level was identified based on the user's performance (response time) and the Yerkes-Dodson Law [155], an empirical law between cognitive performances and arousal in [154].

5.2.2 Physiological input

As for the sensors used in the classification of **AS**, cardiovascular [92, 93, 95, 154], EDA [154], RESP sensors [154] and EEG [92, 93, 154] have proved to contribute to the classification of arousal and valence. Wu et al. classified three arousal levels using EDA, RESP, EEG, ECG measures and SVM [154]. They ordered the physiological signals considering their importance in the classification performance. EDA and RESP features were found to be the most important, EEG features were moderately important (θ waves were the most important ones), followed by ECG features (interbeat intervals features, then HR). Using EEG and ECG features, Marín-Morales et al. found that EEG features were more important than ECG features for both the classification of arousal and valence [92]. Their results are in agreement with Wu et al. [154]'s ones as they found that EEG θ waves played essentially a great role in the classification of emotions [92]. In another study, Marín-Morales et al. also compared the classification of the two emotional dimensions in a virtual vs. in a physical museum environment and found out the classifier for the virtual environment needed fewer features than the classifier for the physical environment [93]. They also tested the classification of emotional valence and arousal using a "baseline" which induced a range of the emotions they targeted, using the IAPS, and the four emotional VEs used in the previous study [92] (see Fig. 5). By concatenating these baseline features to the tested condition features (i.e., features map), they improved the classification in both the physical (using the IAPS features) and virtual (using the four emotional VEs features) setups. Eye movements were also used to recognize the excitement trend (increase or decrease) in VR [2].

For **CS**, EEG [150], fNIRS [121], HR [39] and EDA [39] have been explored to classify different cognitive load levels in IVEs. In contrast to the recognition of emotions for which EEG θ waves were especially important [92, 154], Tremmel et al. found that the most consistent EEG features signals across participants to discriminate the cognitive load levels were the frontal β and γ signals [150]. Using the sensors separately, Collins et al. results showed greater cognitive load classification performances using HR than EDA features [39] (i.e., 91.71% vs. 50.83% in the

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best classification setup). Their classification of two moments of insight however reached a high accuracy using EDA features (i.e., 83.65% in the best setup).

To conclude, previous results in these studies are encouraging for the use of physiological computing in VR. However, most of them were presented using a user-dependent approach, which depicts a true challenge for the generalization of the classification of ACS using physiological signals between users. While interesting, findings for the ACS recognition in VR have to be considered carefully as there is still currently little studies on this topic. No consensus exists regarding which sensors to use for the classification of ACS, and on which classifier to use in particular, in a VR setting where users are prone to motion sickness. The studies also used a variety of methods to label their dataset, from the users' ACS subjective measures to the task difficulty levels for CS. Also, few studies exploited their algorithms in real-time to adapt IVEs.

5.3 Exploitation of Affective and Cognitive States in VR

The exploitation of ACS refers to the modulation of IVEs content based on the user's ACS measure or recognition (see Fig. 1). Table 2 details studies making an exploitation of ACS in real-time. We retained 13 studies that dealt with the exploitation of ACS in IVEs. However, two studies presented a framework of IVEs adaptation based on users' ACS and did not propose an example of possible adaptation [39, 82], which is why they are not presented in Table 2. The methods to exploit ACS measures in real-time can be divided into 2 categories:

- **Explicit exploitation**: the user's ACS measures are used to adjust the IVE content and parameters, to raise awareness by the users about their own ACS.
- **Implicit exploitation**: the user's ACS is measured and used independently from the user's knowledge to adjust the IVE content and parameters.

Explicit and implicit exploitations have several corresponding denominations in the literature. For example, Nacke et al. respectively use the terms "direct" and "indirect physiological control" in the game field [101], and Gilleade et al. use the terms "straight-forward biofeedback" and "affective gaming" [59] for AS specifically.

Among explicit exploitations, a famous category of exploitation is biofeedback. In experiments relying on this type of feedback, users are given indications of their physiological state in the VE or via multi-sensory stimuli. They are, then, encouraged to control their physiological state through feedbacks. This is a type of exploitation which was particularly explored in VR therapy (e.g., [25]) and in 2 studies retained in this survey (i.e., [62, 100]). Another subcategory of explicit exploitations is physiological feedback. It corresponds to the direct display of the users' physiological states to themselves in the IVE interface or to a third party. In this category, users are not particularly encouraged to control their physiological state and the feedback is mostly informative [36, 46, 47].

The target of the adaptation (i.e., the adjusted IVE parameter or content) can take various forms, depending on the targeted ACS and the study objective. As such, task difficulty was often adapted to control cognitive load [48, 115], improve game experience [1], or invite users to control their physiological signals in a horror game (i.e., a biofeedback case) [62]. Another classical category of feedback consists in audio-visual stimuli such as stressors (e.g., explosive device blasts [115], insects spawning [21], music box activation frequency [62], scene occlusion [21, 62]) to control the user's arousal and fear levels. In Muñoz et al.'s study, they used auditory feedback to indicate the cat's location in a rescuing cat game based on the user's physiological signals to encourage users to control their physiological state [100]. The change of avatars appearance [20] and the display of the physiological signals in the user interface [36, 46, 47] was also explored to communicate the users' states to themselves or to another user. Other types of feedback such as olfactory ones or haptic ones were also used to enhance arousal stimuli [115] or as informative indications of the user's physiological state [36, 47].

As for the events used to trigger changes in the IVE content and parameters, ACS recognition was often set as a target method in previous frameworks [23, 26, 39, 82]. However, as seen in Table 2, only two protocols [1, 20] were proposed to adapt VR parameters based on the recognition of ACS using physiological signals and ML methods. Nonetheless, it was not validated through an experimental protocol in the case of Bernal and Maes [20]'s study, and the classification of emotions was not presented in the paper. Abdessalem et al. [1]'s used the excitement and frustration indexes from the Emotiv EEG device as a reference to trigger changes in the game difficulty, which information about the algorithm is still not yet published. This lack of studies doing an adaptation based on ACS recognition can be explained by the difficulty to recognize users' ACS based on physiological signals, as underlined in Section. 5.2. To palliate this issue, other studies focused on determining thresholds based on physiological signals measured during the baseline [48, 62, 100], compared to a normative database [115], or in a custom way per participant [21] to trigger changes in the IVEs. On the other hand, some studies directly projected the users' physiological signals to them [36, 47] or to a collaborator [46] in an explicit way. Bernal et al. also directly used the user's EDA responses in real-time to continuously control the scene occlusion in a horror video [21].

To summarize, some studies adapted IVEs content based on ACS measures knowingly (i.e., explicit exploitation) or unknowingly to users (i.e., implicit exploitation). These adaptations take various forms depending on the targeted changes in users' ACS, from tasks difficulty to haptic and olfactory stimuli. However, few of these studies used ACS recognition as a reference to perform the adaptation, while proposed in many frameworks [23, 26, 39, 82]. Most triggered changes in the IVEs based on physiological signals using a predefined threshold or directly in real-time.

6 Discussion

In this survey, the most common definitions, models, and standard methods to measure ACS in VR were first presented. Then, previous Affective and Cognitive VR studies in IVEs in a non-clinical context were developed following (1) the induction of ACS, (2) the recognition of ACS, and (3) the exploitation of ACS.

AS and CS definitions and models are still the center of debates, which makes the centralization of data and results difficult. This can be explained by the fact that models are mainly theoretical, and hard to prove with the current tools. Furthermore, the definitions and models chosen in IVEs studies are rarely depicted, which can lead to confusions. For example, the term "cognitive load" refers most of the time to the concept of mental

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workload in IVEs and designates another cognitive phenomenon in the psychological field. Thus, we encourage VR studies to clarify the definitions of the targeted AS or CS early in their paper. Emotions (from a dimensional and a discrete perspectives) and anxiety are the AS that were the most studied in VR. Fewer studies dealt with purely cognitive tasks and CS in an IVE, but recent studies show a growing interest in CS such as mental workload.

While there are some distinctions in their definitions and models, AS and CS are closely linked in the methods to measure them [12, 103, 154]. Based on previous categorizations [66, 104], we proposed to divide the methods to measure ACS into 4 groups: self-report, observational, performance, and psychophysiological methods. These methods are not exclusive to IVEs, but the VR context involves some adaptations and care compared to usual methods because of the cumbersomeness of VR equipment, the presence of interactions, and cybersickness (see Section 4). In this survey, most Affective VR studies relied on self-report and psychophysiological measures, and most Cognitive VR studies relied on task performance and observational measures (see Table 1). There is however a trend in recent years as more Cognitive VR studies tend to use psychophysiological signals [39, 121, 150]. Overall, self-report methods have the advantage to show high-face validity but can disrupt the immersion; and observational, performance and psychophysiological methods have the advantage to be continuous, but can be context-dependent and complex to analyze.

In this survey, we retained 63 studies that induced, recognized, and/or exploited ACS in IVEs. Starting with the methods of **induction of ACS**, various IVEs variables were found to influence healthy users' ACS, despite individuals' differences (see Table 1). We gathered the stimuli used in past studies in two categories: (a) studies that aimed to induce different ACS or different levels of ACS, and (b) studies that aimed to study the effect of a parameter on an AS or a CS. As such, in the first category, works mainly used audio-visual stimuli through emotional videos, emotional VEs, emotional scenarios, and cognitive tasks. Among methods that can be considered as standardized, Li et al. developed a database of 73 public immersive 360°panoramic videos to induce different emotions along the valence and arousal dimensions [79]. In another study, Mavridou et al. used 20 videos from an affective film library in an immersive virtual cinema to induce valence (two levels) and arousal (two levels) responses [96]. The virtual pit experience and virtual public speaking situations are also classical experiments that were found to elicit changes in state-anxiety and physiological responses [98, 140]. Otherwise, other studies changed a variety of audio-visual contents in IVEs applications to induce different AS. For the induction of different levels of CS, studies mainly relied on standardized single task difficulty levels variation such as the n-back task [86, 121, 150], spatial rotation task [39], visual search task [48, 58] difficulties, or on multitasking [87, 114]. Cognitive tasks also were found to increase the user's arousal level [6, 114, 154]. These studies demonstrated the fact VR can be a strong ACS inducer. In the second category, other factors such as the type of display, the level of immersion, avatars, personality traits, redirected walking, and multi-sensory feedback were found to influence ACS.

As for the **recognition of ACS**, IVEs studies mainly relied on physiological signals and ML algorithms (see Table 3). The passive recognition of ACS is promising given the growing interest and recent performances of ML algorithms but can be tricky because of individual differences, the fact responses can be context-dependent, and because of the necessity to have large labelled datasets. For now, models of recognition of ACS in IVEs have shown great performances (see Table 3). However, they were mostly evaluated following user-dependent approaches. The recognition performance of user-independent models (i.e., the generalization of recognition on unseen participants) was rarely explored. The field could benefit from large datasets (e.g., ImageNet for object recognition using deep learning), which can be difficult to acquire given the anonymity issues, the setup time and expenses required by VR and physiological equipment. In conclusion, previous results in the recognition models of ACS in IVEs are hardly generic but pave the way for future works. The recognition of users' ACS could allow the automatic adaptation of IVEs based on the user's ACS without the need to disrupt the immersion by asking users to self-report their mental state.

Two types of **exploitation of ACS** were identified from existing affective and cognitive VR studies in the scope of this survey: (1) explicit exploitation and (3) implicit exploitation. Among the few studies which presented an adaptation of IVEs parameters based on users' ACS, half validated their methodology with an experimental protocol (see Table 2). Most of these studies have set physiological thresholds as reference events to trigger changes in IVEs content based on the user physiological signals. Despite the presentation of frameworks that integrate the recognition of ACS to trigger changes in VR content [39, 82], only two proposed an adaptation based on ACS recognition: one without experimental validation [20], and one, based on Emotiv excitement index [1]. This can be explained by the difficulty to recognize ACS and interpret ACS responses.

7 Research Perspectives

Those studies demonstrate the will to build more user-centered IVE applications by taking into account the user's ACS. Most works focused on the induction of ACS, followed by a few works in the exploitation of ACS, and finally the recognition of ACS. This can be explained by the fact ACS was mostly used as an offline metrics as a way to evaluate the user experience. The recognition of ACS can be complex to achieve as studies rely on Supervised ML, which usually require a high quantity of data and complex signal processing for physiological data. As for the exploitation of ACS, there are a few more studies than in the recognition of ACS as the feedback can be based on the features of the physiological signals directly.

Most studies used a combination of many factors such as light, colours, presence of 3D objects, characters appearance and behaviour, and music to induce multiple emotions or emotions variations. The effect of each of these factors individually is not clearly understood, which could be interesting to explore. Moreover, only emotional panoramic videos were used to develop standardized stimuli databases [79, 96] for emotional valence and arousal. Interactivity is an important component of VR [144], and certain interactions were already found to impact the user's ACS [11, 109]. Thus, developing standardized methods which introduce interactions with 3D entities to induce different ACS could be interesting to fully exploit VR engagement power. Also, some factors linked to the users' profiles were found to have a significant effect on the stimuli influence [5, 55, 117]. More works studying the effect of personality traits and cognitive abilities on

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the impact of ACS stimuli could help understanding how to make VR application more adapted to users.

Indeed, individual differences are one of the main issues in the recognition of ACS. Studying methods to normalize physiological data and subjective responses could help make the recognition models more generic. There is also no work yet targeting the genericity challenge, demonstrating the performance of a recognition model on unseen participants in a different context than in the one the model was trained. Another problem is that studies recognizing CS mainly used indirect methods to label their datasets, such as tasks difficulty levels and tasks performances data. A task can induce different mental workload levels to the users. In the same way, different users showing similar task performances might experience different mental workload levels as seen in [48]. Overall, we would suggest the use of self-report methods for the labelling of datasets as they show a higher face validity than other metrics (see Section 4).

As for the exploitation of ACS, there is currently a lack of experimental validations of the proposed exploitation. There is also no proposition of adaptation models based on ACS in IVEs. Future works could focus on presenting new adaptive models, to determine what type of content should be adapted based on the nature of the detected ACS, on demonstrating them, and on studying their impact on users in IVEs. Furthermore, the implicit exploitation of ACS based on the recognition of ACS was very little explored as the recognition of ACS tend to be complex. This is an important path for future work to build more user-centered applications as taking into account the user AS and CS is going to provide more robust and adapted immersive experiences to the users' individual differences.

8 Conclusion

In this paper, we defined Affective and Cognitive VR to relate to works that (1) induce affective and cognitive states (ACS), (2) recognize ACS, or (3) exploit ACS in VR. First, the different definitions, models, and standard methods to measure ACS in VR were introduced and discussed. Then, we presented a survey of previous Affective and Cognitive VR works in Immersive Virtual Environments (IVEs) in a non-clinical context. Methods that induced ACS were largely explored in the literature. Those were categorized into several groups, mainly studies that aimed to induce different ACS or several ACS levels, and studies that focused on the influence of a parameter on an AS or a CS. As for the recognition of ACS, methods mainly used supervised machine learning and physiological signals. Previous work results are promising but are hardly generic. Finally, the exploitation of ACS can be divided into 2 groups: the modulation of IVEs knowingly to users (i.e., explicit exploitation) or unknowingly to users (i.e., implicit exploitation). Most works used physiological signals features directly or through thresholds to trigger changes in the IVEs and only half validated their adaptation proposition with an experimental protocol. Taken together, these studies pave the way for future Affective and Cognitive VR work, for which we provide different research perspectives.

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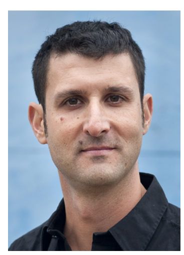

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