Survey of Affect Representation Schemes in Physiological Automatic Affect Recognition

A Systematic Literature Review

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Abstract

Physiological signals, such as Electroencephalogram (EEG), Glavic Skin Response (GSR), or Body Temperature, are common inputs for Automatic Affect Recognition (AAR) systems. One of the crucial elements of AAR is the Affect Representation Scheme (ARS) used to define the affective states recognized by the system (e.g., happiness, sadness, fear, anger). Throughout the years many AAR reviews have been published. However, most of them do not include a detailed analysis of ARSs and the motivation behind them. This paper aims to fill this knowledge gap by performing a Systematic Literature Review (SLR) of Computer Science papers that propose a Physiological-signal-based AAR (PAAR) system. We explore how researchers discuss and choose an ARS and whether they base it on actual psychological theories. Eligible papers are retrieved from 4 databases: Web Of Science, IEEExplore, Scopus, and ACM Digital Library. Due to time limitations, the review is done rapidly and some additional search constraints are applied for feasibility. The most significant restrictions are: considering papers published since 2020 and performing experiments on specific benchmarking datasets. We take these constraints and their possible impact into consideration when interpreting the results. The presented review procedure can be stripped from the additional filters and reused for a full review. In total 115 papers are processed. The majority of papers introduce an EEG-based emotion recognition system. The analysis of the extracted information reveals that dimensional ARSs, in particular, Valence/Arousal model is the most popular. Moreover, authors often choose to reduce the dimensions to high/low values. Categorical ARSs are less frequent and usually are adopted from the dataset. Lastly, the authors do not provide extensive motivation for the choice of ARS and rarely refer to psychological theories.

Abbreviations

ACC	Accelerometer	EDA	Electrodermal Activity	GSR	Glavic Skin Response
BVP	Blood Volume Pulse	EEG	Electroencephalogram	EOG	Electrooculogram
ECG	Electrocardiogram	EMG	Electromyogram		

1 Introduction

Automatic Affect Recognition (AAR) are systems that determine a human's affective state. AAR has numerous applications. In Artificial Intelligence (AI) emotion recognition is part of human-robot interaction and therefore highly contributes to advancements in AI [1]. Psychiatrists could use such systems for diagnosing mental disorders [2]. Even in the gaming industry, a game that responds to the player's affective state improves their experience [3]. More examples can be found in education, marketing, and software engineering [3]. With this wide range of applications, AAR becomes an attractive and promising field of study.

There are many modalities that can be used as input for AAR. Physiological signals are a particularly interesting case. These signals include all internal body conditions that change depending on a person's affective state. Some examples are: Body Temperature, Electrocardiogram (ECG), or Conductive Skin Response [4]. Barely a decade ago emotion recognition using physiological signals has been still considered a new topic that had been just starting to develop [5]. Throughout the years it has gained more interest among researchers [6]. One of the reasons is the recent developments in wearable personal devices [6] such as smart bands, smartwatches, or sensorized t-shirts [7][8]. Gathering data for Physiological-signal-based AAR (PAAR) used to be demanding and unpleasant for a user as it required special equipment [3]. Wearable devices collect physiological data in a non-intrusive, user-friendly way. That has become a strong advantage of PAAR [9]. Moreover, physiological signals are often said to give more truthful results than other modalities as they are difficult to control unlike external signals such as facial expressions [4][10].

In this paper, affect is defined as "a general sense to refer to a class or category of mental states that includes emotions, moods, attitudes, interpersonal stances, and affect dispositions." [11]. Looking at this definition it can be seen that there are multiple affect phenomena. The most obvious category is emotions. Their main outstanding characteristic is that they are event-driven, so they are triggered by a stimulus (e.g., video, memory) [12].

Affect Representation Scheme (ARS) is a method of defining affective states and a critical element of every AAR system. Choosing an ARS for AAR is challenging because it is difficult to realize how many and what kind of different affection states the algorithm has to account for to give precise and meaningful results [3]. The fact that even psychologists fail to give a definite universal affect representation [13] shows how complex this topic is. It has been mentioned in the literature that the ARS not only has an impact on the entire system but also on how easy it is to compare it to other solutions [7]. Some of the more recent papers, mention the importance of ARS in AAR research [2], [14]. Following this trend, this paper performs a review of PAAR systems focusing only on ARSs.

The results of this Systematic Literature Review (SLR) of ARSs used in PAAR can be useful for both Computer Science and Psychology. Psychologists can get an overview of what ARSs are used without reading technical Computer Science papers. In their work, they can also address the challenges of ARSs in PAAR and therefore contribute to PAAR research. Computer Scientists who are developing their own AAR system might find this paper helpful when choosing an ARS. SLR methodology is recommended for research where the same type of information from different studies is extracted, aggregated, and compared. It also reduces the bias of the researcher performing the review [15] which is extremely important as there is only one reviewer in this project.

While studying the existing reviews on AAR using physiological signals, no work has been found where the motivation behind the choice of an ARS was discussed. Similarly, we did not encounter any example of examining the collaboration between the targeted affective states and the chosen ARS. Rarely do reviews include discussions on the trends or popularity among different ARS. This paper will aim to fill in this gap in the literature. The scope of this review is defined by formulating a research question as well as 8 Sub-questions (SQs). These sub-questions together with their justifications are presented in Table 1. Sub-questions 1-7 were given by the project description. Question 8 was added by the author.

Research question:

What Affect Representation Schemes are used in Physiological-signal-based Automatic Affect Recognition systems that are described in the existing literature?

Table 1: Sub-questions (SQs) that will help answer the main research question and their motivations.

Sub-question	**Motivation**
SQ1: *What different types of input data do prediction systems use for their analysis?*	There is a huge variety of signals that can be used for PAAR systems. These signals influence the entire system and therefore can have an impact on the choice of the ARS.
SQ2: *What types of affective states have been targeted by prediction systems (e.g., only emotions or also mood)?*	As discussed earlier there are different kinds of affect phenomena. Depending on which one is targeted by the system a different ARS could be chosen.
SQ3: *What different ARSs have been used for this, and if so, what is the motivation for this particular scheme?*	This is the main question of the review. The aim is to not only gather information about commonly used schemes but also the motivations given by the authors.
SQ4: *Are systems using more than one ARS, simultaneously and if so, what is their , motivation for doing so?*	It is possible that some systems will use more than one ARS. It is interesting to explore why schemes are used together.
SQ5: *Are there differences in the popularity of ARSs used for modeling different affective states?*	Following up on SQ2 and SQ3, in this question the correlation between ARS and target affect state will be investigated.
SQ6: *Has the popularity of specific ARSs changed over time?*	The popularity of an ARS can be influenced by many advancements in research such as the publication of a new dataset or psychological paper on defining a new ARS. Therefore, we analyze the papers also by their year of publication.
SQ7: *Is the majority of ARSs used based on psychological theory?*	It is expected that the authors of the papers included in the review are not psychologists. Therefore, their work has to be compared against existing psychological theories.
SQ8: *Are there differences in the popularity of ARSs used for particular signals?*	Following up in SQ1 and SQ3 the correlation between the input signals and chosen ARS is researched.

In this review, the considered sample of papers consists mainly of EEG-based emotion recognition which limited the answers to some of the SQs. The results indicate that dimensional high/low approaches in particular Valence/Arousal model is the most common ARS. Authors often simplify the dimensional ARSs of datasets by ignoring some dimensions or reducing them to high/low values. The categorical ARSs are modified less frequently. The most common set of categories is *positive, negative, (neutral)*, however, recently, larger sets of categories have gained popularity. We also find that the motivation for ARSs and psychological background is often lacking in the reviewed papers.

The paper is organized as follows. Section 2 presents the methodology developed for this review clearly separating the constraints for feasibility. The results of extracted information analysis are shown in section 3. Next, section 4 reflects on the ethical aspects and reproducibility of the review. The results of the review are discussed and interpreted considering the limitations in section 5. Lastly, conclusions and recommendations for future work are stated in section 6.

2 Methodology

The paper is structured according to PRISMA guidelines [16]. As required by the project the literature review will be performed in a systematic manner described in detail in [15]. In SLR before diving into papers a strategy for searching, selecting, and reviewing articles is developed. One of the initial steps is a scoping search. In total 15 existing surveys of AAR were processed. 8 of these papers were considering only physiological signals and the remaining 7 reviewed also other types of signals along with physiological ones. The entire review is done by one reviewer.

Firstly, the eligibility criteria for a paper to be included in the review are formulated in section 2.1. The queried search engines are discussed in section 2.2. The actual search strategy used to build a query including the constraints for feasibility is presented in section 2.3. In section 2.4 the selection process of retrieved papers is described. Section 2.5 talks about data extraction and synthesis. Lastly, search results are presented in section 2.6.

2.1 Eligibility criteria

Inclusion and exclusion criteria in a systematic literature review are the properties that either make the paper eligible or disqualify it from the review [15]. Properly defined criteria allow fast evaluation of a paper and decision if it should be included or not. In this review, the following criteria were formulated:

Inclusion Criteria:

- Paper introduces an AAR system (*the focus of this paper*)
- System uses at least one physiological signal as input for the AAR system (*the focus of this paper*)
- Paper is from the Computer Science field (*targeting papers that design the system*)

Exclusion Criteria:

- Paper describes or aggregates information about more than one system or group of systems (*excluding reviews and surveys*)
- Paper focuses on comparing the performance of different signals, features, or other components of the system that do not concern ARS (*excluding papers that do not focus on developing a new PAAR but on improving the efficiency of existing solutions*)
- Paper is presenting an improvement of an algorithm and the improvement does not concern the affect representation scheme (*excluding papers that do not focus on developing a new PAAR but on improving the efficiency of existing solutions*)
- System does not recognize/predict human affect
- Paper is not written in English
- Paper is not published in a journal or a conference proceeding paper or as a book chapter (*excluding papers such as corrections or letters*)

2.2 Search Engines

Papers for the review are collected on May 31st 2023 from 4 databases: Scopus[1], Web of Science[2], IEEE Xplore[3], and ACM Digital Library[4]. The first two databases were chosen because they are often seen in the reviews and include useful filtering options such as filtering by topic. IEEE Xplore and ACM Digital Library are more specialized databases, so they also had to be included. For example, IEEE Xplore posts many papers in the field of computer science and publishes journals on Affective Computing. Therefore, this database had to be included in the search.

2.3 Search Strategy

In this review, we are looking for papers that present automatic recognition systems based on physiological signals. In particular, sections regarding ARS are taken into consideration. To construct queries

[1] https://www.scopus.com
[2] https://www.webofscience.com
[3] https://ieeexplore.ieee.org
[4] https://dl.acm.org

to search for the target papers, three key terms: ***affect***, ***recognition***, and ***physiological signals***. These terms will be searched in the title, abstract, and keywords. A fourth term, ***review***, is searched in the titles with a *NOT* operator to exclude reviews and surveys from the search. The overview of all terms and their synonyms used in the queries is presented in Table 2. Terms related to ARS are not included. This would exclude the papers where ARS is not discussed. Therefore, this term in the query could eliminate valuable papers from the search and influence the results of the review. Queries for specific search engines can be found in Appendix A.

Table 2: Four terms and their synonyms used to construct the queries for each search engines to generate a list of papers that can potentially be used in this review. Note: *review* term is queried with a *NOT* operator.

affect	affect*, emotion*, mood, mental state, happy, anger, sad, disgust, fear, arousal, valence, dominance
recognition	recogni*, predict*, detect*, classif*
physiological signal	physiolog*, bio-signal, biosensors, emg, electromyograph*, gsr, glavic, ecg, electrocardiogram, eeg, electroencephalogram, cardiovascular, respirat*
review	review, survey, compar*

Feasibility filtering

A full SLR takes more than 10 weeks. Therefore some constraints for feasibility have to be applied. It is important to carefully choose these constraints so that the results are still representative and used in future work. The first filter is constraining the review to papers published only in 2020 or later. This will limit the answer to SQ6 which concerns the popularity of schemes over time. However, if the review was to be continued the papers from this period could be excluded, so this paper can still make a meaningful contribution to the full review. Another filter that was applied at the query level is excluding the papers that are not testing their systems on well-known benchmark datasets. Therefore, we add term ***dataset*** to the queries. This term will also be searched in the title, abstract, and keywords. Table 3 presents this term together with the datasets found in the existing review papers. The queries updated with these two feasibility filters can be found in Appendix B.

Table 3: Additional term for constructing the query added for feasibility. Addition to the terms from Table 2.

datasets	DEAP, AMIGOS, ASCERTAIN, BIO-VID_EMO DB, DREAMER, MAHNOB-HCI, MPED, SEED, Eight-Emotion, DECAF, USI_Laughs, Driver, Non-EEG, Distracted Driving, WESAD

2.4 Selection Process

After generating four lists of papers (one from each database) the papers have to be filtered to determine if they fulfill the eligibility criteria. The first step is removing the duplicates. After this is done the papers are filtered on the title. If it is clear based on the title that the paper is not suitable for this review it is excluded. The next step is similar, but instead of titles, we consider abstracts.

In a standard SLR the next step is to retrieve the papers and assess them based on the eligibility criteria. The remaining papers are included in the review. However, to adjust to the time constraints these last two steps together with data extraction described in the next section are done in an iterative way. Papers are randomly split into subsets. In every iteration, we attempt to retrieve the subset of papers and assess their eligibility based on full text and then extract the relevant information from every paper. This approach gives us the flexibility to pause the extraction after any iteration and proceed to the synthesis of results.

2.5 Data Extraction and Synthesis

The papers that survive the manual filtering are moving on to the data extraction phase. Before diving into the literature we have to determine what data has to be retrieved from the papers to answer all SQs. Table 4 lists the information that is extracted from every paper as well as related sub-questions. For each paper, this data is collected in an Excel sheet that will make it easier to process in the next phase.

Table 4: Data to be extracted from every paper included in review, example results, and related SQ (sub-question)

Information		SQs
Year of publication (2020-2023)		6
What signals are used as input (e.g. EEG, ECG, RSP)		1, 8
What dataset(s) is used?		1, 3
Target affection states (e.g. mood, emotion)		2, 5
ARS	Dimensional/Categorical/other?	3, 5, 8
	If dimensional, what dimensions are used? (e.g. arousal, valence)	3, 5, 8
	If categorical what categories are considered? (e.g. happy, sad)	3, 5, 8
	What is the motivation (if there is any) for using this scheme(s)? (e.g. popularity, database)	3
	Is any psychological work mentioned (e.g. Russell, Ekman)?	3, 7
	Is the choice of the scheme motivated by non-psychological work?	3, 6
	Are multiple schemes used?	3, 4
	What is the motivation for using multiple schemes simultaneously? (e.g. multiple datasets)	4

To answer the research questions the data extracted from the papers has to be processed into useful information. Depending on the research question the papers are grouped for analysis. For example, to answer SQ6 the papers that were published in the same year are collected. For every group, the number of occurrences of every ARS is calculated and reported.

2.6 Search Results

This subsection gives the results of applying the methodology described in the previous subsections. The feasibility filters have drastically reduced the number of papers obtained, a detailed breakdown can be found in Appendix C. The results of paper selection, retrieval, and filtering is summarized in Figure 1 which is adapted from PRISMA [16]. Applying the developed methodology resulted in 115 papers being included in the review.

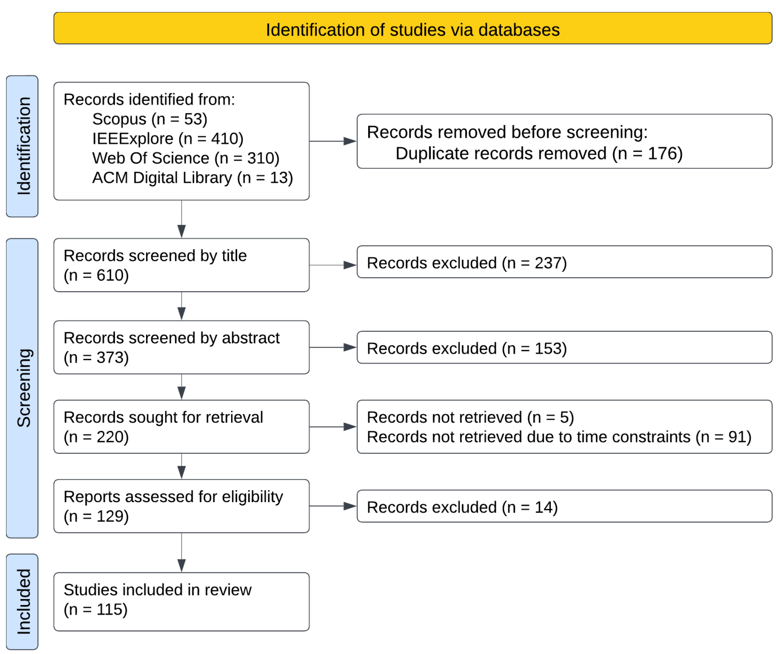

Figure 1: Adapted PRISMA diagram.

3 Results

This section presents the results of the analysis of information extracted from the reviewed papers ([17–131]). In section 3.1 we give an overview of the datasets used in the papers. Each of the remaining sections corresponds to a research sub-question. Additional background information is provided where necessary. Section 3.2 presents the most common physiological input signals (SQ1). Next, we introduce different categories of affect and present which categories are targeted by the reviewed papers (SQ2) in section 3.3. Section 3.4 explains the types of ARSs and provides some well-known examples. We also discuss the most common motivations for the ARS and ARS types (SQ3). PAAR works that use multiple ARSs (SQ4) are analyzed in section 3.5. We assess the ARS popularity in relation to the targeted affect category (SQ5) and year of publication (SQ6) in sections 3.6 and 3.7 respectively. Section 3.8 presentss how many papers base their ARS on psychological theories (SQ7). Lastly, we explore the correlation between the physiological input signals and ARS used in PAAR (SQ8) in section 3.9.

3.1 Datasets

Before answering the research questions the datasets used in the included papers have to be discussed. They might have a significant impact on the results and therefore have to be taken into consideration when interpreting the findings. Authors of datasets collect a group of subjects and present each individual with a stimulus while monitoring their physiological signals. Each subject self-assesses their affect state triggered by the stimulus. Sometimes affect is also noted by an observer. Table 5 gives an overview of datasets that were used in the reviewed papers as well as the number of papers that utilized each dataset. A full list of common dataset combinations can be found in Appendix D.1.

Table 5: Summary of the datasets that were specified in the query (Table 3) and were found in the reviewed papers.

Ref.	Year	Dataset	ARS type	Affective States	Physiological signals	Number of papers that use this dataset	Number of papeprs that use this dataset exclusively
[132]	2012	DEAP	dimensional	Arousal (1-9), Valence (1-9), Dominance (1-9), Liking (1-9), Familiarity (1-5)	EEG, GSR, Respiration Amplitude,Skin Temperature, ECG, Blood Volume (pletysmograph), EMG, EOG	80	46
[133]	2018	DREAMER	dimensional, categorical	Valence (1-5), Arousal (1-5), Dominance (1-5), + specify thresholds for categories: anger, fear, sadness, disgust, calmness, surprise, amusement, happiness, excitement	EEG, ECG	21	2
[134]	2012	MAHNOB-HCI	dimensional	Valence, Arousal, Dominance, Predictability (discrete scales 1-9), emotional keywords: sadness, joy, disgust, neutral, amusement, anger, fear, surprise, anxiety	EEG, GSR, ECG, Respiration Pattern, Skin Temperature	9	0
[135] [136]	2015	SEED	categorical	positive, negative, neutral	EEG	29	12
[137]	2019	SEED-IV	categorical	happiness, sadness, fear, neutral	EEG	7	1
[138]	2021	SEED-V	categorical	happy, sad, disgust, neutral, fear	EEG	2	1
[139]	2021	AMIGOS	dimensional, categorical	Valence, Arousal, Control, Familiarity, Liking and basic emotions, PANAS, Big-Five Personality Traits, extrenally assessed valence and arousal	EEG. ECG, GSR	10	3
[140]	2018	ASCERTAIN	dimensional	Arousal(0,6), Valence (-3, 3), Engagement, Liking, Familiarity + Big Five personality Traits	EEG, ECG, GSR	1	1
[141]	2018	WESAD	categorical	Neutral, Stress, Amusement	BVP, ECG, EDA, EMG, Respiration, Body Temperature,ACC	3	3
[142]	2001	Eight-Emotion	categorical	Neutral, Anger, Hate, Grief, Platonic Love, Romantic Love, Joy, Reverence	ECG, EDA, EMG, Respiration	1	0
[143]	2019	MPED	categorical	Joy, Arousal, Anger, Fear, Disgust, Neutrality	EEG, ECG, RSP, GSR	1	0

Among the reviewed papers the most common dataset is DEAP. Authors often note that it is widely used for PAAR. In comparison to other described datasets, DEAP considers the highest number of signals and was published relatively early. Therefore, authors who would like to conduct a comprehensive evaluation of their PAAR system, are likely to choose DEAP.

3.2 Input data

There is a huge variety of signals that can be used as input for PAAR. The existing review papers mention many advantages of EEG. This type of signal is considered to be essential in PAAR as it gives precise results and is often used in the datasets [4], [6]. Other signals include EMG, ECG, GSR, and Respiration features. To increase the reliability and effectiveness of a PAAR system it is recommended to apply a multimodal approach, which means to include multiple physiological signals [144]. The optimal set of signals has not been determined [6], however, their selection depends on the operating environment of PAAR. For example, in laboratorical conditions, EEG, EMG, ECG, or BVP might give the most accurate results while considering a wide range of emotions [144].

The input signals used in the reviewed papers are summarized in Table 6. By far the most popular signal is EEG. Other less popular signals are GSR and ECG. Only ECG and EEG were used as exclusive physiological input signal. 93 papers used only EEG and 3 papers used only ECG. The remaining signals were always used in multimodal systems. These results imply that the conclusions made in this review concern mainly EEG-based systems due to the lack of representation of systems using other physiological signals within the sample of papers.

Table 6: Physiological signals used in the reviewed papers. (Blood Volume measured by plethysmograph)

Signal	Number of papers	Papers
EEG	108	[17], [19–22], [24], [25], [27–49], [51–71], [73–80], [82–101], [103–131]
GSR	13	[19], [22–24], [35], [69], [72], [87], [94], [101], [102], [122], [131]
ECG	12	[17], [18], [22], [26], [50], [59], [72], [87], [94], [101], [102], [131]
Respiration	6	[24], [69], [72], [101], [102], [122]
EMG	5	[23], [24], [101], [102], [122]
EOG	4	[19], [69], [101], [122]
Skin Temperature	4	[24], [101], [102], [122]
Body Temperature	2	[72], [81]
PPG	2	[19], [72]
BVP	2	[23], [81]
Blood Volume	2	[101], [122]

3.3 Affect Categories

Emotions are the most evident type of affect. Scherer defines several affective phenomena that should be distinguished from emotion: preferences, attitudes, mood, affect dispositions, and interpersonal stances [12]. Wearable devices are now a promising and developing direction for PAAR. In the search query, we have included datasets that are specifically created for wearable devices. Most of them also include stress-related labels. For example, WESAD [141] was designed to detect stress and affect. Therefore, we also recognize stress as a separate category. However, we acknowledge that it is not clear if it can be considered an affective phenomenon. Therefore, we do list it as one of the affect categories, but analysis of stress detection systems is outside of the scope of this review.

For every reviewed paper the target affect category was noted. The results were summarized in Table 7. Majority of the reviewed papers focused on detecting emotions. Some papers considered emotion in a specific context. For example, [85], [91] detect emotions of hearing impaired subjects. We decided to separate those works from general emotion recognition systems so that we can later investigate the differences between their ARSs. On the other hand, two authors decided to tackle multiple affect categories, namely, emotion and stress. Others consider only stress or try to address affect in general. Only one paper considers mood. An interesting case is a paper [49] which claims to be targeting emotion and stress and uses datasets that do not target stress (DEAP [132] and SEED [135][136]. These results imply that the conclusions of the review concern mainly emotion recognition systems due to the lack of representation of systems targeting other affect categories within the sample of papers.

Table 7: Target Affect Categories identified in the reviewed papers.

Target Affect Category	Number of papers	Papers
emotion	99	[17–22], [24–26], [28–48], [50–66], [68–71], [74–80], [82], [84], [86–90], [92–94], [96–99] [101], [103], [105–110], [112–117], [119–131]
emotion in specific context	9	[23], [67], [73], [85], [91], [95], [104], [111], [118]
multiple affect categories	2	[49], [72]
stress	2	[81], [102]
affect	2	[83], [100]
mood	1	[27]

3.4 Popularity of ARSs and given motivations

Background

There are two main categories of ARSs. Categorical schemes define a finite number of distinct affective states [145]. The second type is dimensional schemes that describe affect as a point in a multi-dimensional space [146]. It is important to note that there exists a connection between the two types of ARSs, for example, categorical representations can be translated to a dimensional representation [9].

A well-known categorical ARS was proposed by Ekman in 1971. He included 6 basic categories for emotion: *happiness*, *sadness*, *disgust*, *fear*, *surprise*, and *anger* [147]. Plutchik added *anticipation* and *trust* and created a Plutchik wheel of emotion [148]. In 1988 Watson also suggested that affect measured on a scale from positive to negative [149]. Russel proposed a two-dimensional circumplex Valence/Arousal (VA) method of classifying affect [150]. Later together with Mehrabian, they added one more dimension, namely Dominance creating a VAD model [151]. An interesting ARS was proposed by Verma in 2017. The points in the Valence/Arousal/Dominance space are clustered into 5 groups of emotions [152].

One existing review ([153]) discusses emotion representation models in physiological emotion recognition in more detail. However, it was published in 2015, so the information gathered there might be outdated. In 2015, dimensional models based on a subset of Arousal, Valence, and Dominance were more popular than categorical models [153]. The paper concluded that authors rarely give specific definitions of states targeted by the system. Categorical models are considered to be the easiest approach as long as the number of states is not too high [153]. The most common categorical model is Ekman's model [145] or custom models [153]. More recent work has stated that applying non-standard self-made models is still in practice [7].

Review results

The results are presented in two steps. The first categorization of the papers is based on the type of ARS. In this work, we distinguish 3 types of ARS: dimensional, categorical, and combination. The combination type includes schemes that have both dimensional and categorical characteristics. For example, two-dimensional space is divided into quadrants which are given a label. The next step is to take a closer look at every type of ARS and the specific representations that are used. Along with the popularity we discuss the most commonly used justifications for each ARS and ARS type. Motivating the choice of ARS can be done by discussing previous works. Overall, 20 papers ([17], [21], [24], [32], [49], [66], [73], [75], [80], [95], [100], [101], [104], [105], [107], [109], [121], [122], [124], [129]) referred to previous works done by other researchers to motivate their choice of a particular ARS.

Table 8 gives an overview of the types of ARSs used in the reviewed papers. By far the most common type is dimensional, however only 6 papers [19], [44], [75], [76], [92], [105] motivate this decision. Their authors explain that dimensional ARSs surpass categorical ARSs because they can express more states and are better at capturing subjective and uncertain affect. The remaining papers using dimensional ARS do not include any specific arguments for this type of scheme. Similarly, other types of ARS are usually not motivated.

Table 8: Types of ARSs in reviewed papers.

Type	Number of papers	Papers
dimensional	68	[17], [19–22], [24], [26], [27], [29], [31–33], [36], [37], [39–41], [43–45], [47], [50], [52], [54–56], [58], [59], [61], [63], [65], [70], [73–76], [82], [83], [86], [87], [89], [90], [92–101], [104–107], [109], [110], [114–117], [119], [121], [122], [124], [129], [131]
categorical	23	[23], [30], [34], [38], [42], [48], [51], [66], [71], [72], [77–81], [84], [85], [88], [91], [102], [111], [127], [130]
combination	11	[18], [35], [60], [64], [67], [69], [103], [113], [118], [120], [123]
dimensional, categorical	9	[25], [28], [46], [57], [68], [108], [112], [125], [126]
categorical, combination	3	[49], [53], [62]
not specified	1	[128]

Dimensional ARSs used in the reviewed papers are presented in Table 9. Authors rarely give any motivation for the choice of dimensions. The most popular argument that was used by 14 papers ([19], [21], [36], [39], [40], [54], [55], [58], [61], [73], [94], [95], [104], [105]) to justify the VA dimensions was the popularity of this scheme. One paper ([107]) gives the same motivation for the VAD dimensions. Some PAAR systems limit their systems to detecting valence, but only one of them mentions that it was done for simplicity [20]. Other dimension sets were not motivated. A common practice is to simplify each dimension of ARS into High/Low values. Usually, no motivation for this decision is given other than simplicity and popularity.

Table 9: Dimensions for ARS in reviewed papers. H/L - ARS where affect is described as a High/Low value in each dimension (for example High/Low Arousal). Num. - ARS where the affect is described as a numerical value in each dimension. (V-valence, A-arousal, D-dominance, L-liking)

Dimensions	H/L	H/L papers	Num.	Numerical papers	Total
VA	39	[22], [25], [29], [31], [36], [39], [43], [47], [50], [52], [54], [55], [58], [65], [68], [70], [73–75], [83], [87], [89], [90], [94], [98], [101], [105], [108–110], [112], [114], [115], [117], [119], [121], [124–126]	16	[19], [21], [26], [32], [33], [37], [40], [41], [45], [46], [61], [86], [95], [116], [122], [131]	55
VAD	11	[17], [28], [44], [59], [76], [92], [93], [99], [100], [106], [129]	3	[57], [96], [107]	14
VADL	2	[24], [56]	2	[96], [97]	4
V	2	[20], [63]	1	[82]	3
PANAS	0	-	1	[27]	1

Table 10 presents the most common categorical ARSs. They are usually inherited directly from the dataset. The number of categories varies between 2 and 8. The papers using the same category sets are the result of authors choosing the same dataset for their experiments. Most popular datasets are SEED [135], [136], SEED-IV[137], and SEED-V[138]. It can be assumed the authors' motivation for using these ARSs is the dataset, however, it is rarely stated explicitly. An interesting label that many papers include in their ARSs is 'neutral'. It is also included in the mentioned datasets. Authors of SEED explain that in comparison with a negative state, subjects in a neutral state are more relaxed and inattentive [136]. We have decided to group together papers that ARSs differ only by this label.

Table 10: Categorical ARS in the reviewed papers.

Categories	Number of papers	Papers
positive, negative, (neutral)	28	[25], [28], [30], [34], [38], [46], [49], [53], [57], [62], [71], [77–80], [51], [66], [68], [84], [85], [88], [91], [108], [112], [125–127], [130]
sad, happy, fear (neutral)	6	[30], [48], [53], [77], [79], [111]
sad, happy, fear, disgust, (neutral)	2	[42], [48]
other	7	[23], [46], [49], [72], [81], [102], [111]

The combination ARSs are made by the authors of the reviewed papers, so these results cannot be summarized in a table. An interesting case is [35] which presents a system that produces probabilities of valence and arousal being high or low. These results are used to calculate numerical values for the two dimensions. Lastly, the system translates the values into a categorical label (6 emotions + neutral). The authors motivate this ARS by the universality of Ekman's model, the popularity of the VA model, and the simplicity of high/low approaches. Another example is [62] which refers to previous works and splits the valence dimension from DEAP [132] into 3 categories negative (V<3), positive (V>7), and neutral (3<V<7).

3.5 Multiple ARSs

Performing experiments on multiple datasets allows authors to compare their systems to existing solutions. That usually means that they have to adapt different ARS for every experiment. Another solution to this problem is using a combination ARS where the labels from the datasets are translated to the ARS used by the system. However, these translations should be based on psychological theories and motivated by the paper.

20 papers ([25], [28], [30], [46], [48], [49], [53], [57], [60], [62], [68], [77], [79], [96], [102], [108], [111], [112], [125], [126]) use multiple ARSs. All of them used a different scheme for every dataset. In [102] authors also use different schemes for different experiments on the same dataset. The purpose of this was to find the ARS where the system achieves the highest prediction accuracy.

3.6 ARSs for different affect categories

One of the research questions concerns the popularity of ARSs used for PAAR targeting different affect categories. Figure 2 presents how often each type of ARS was used for every category. The majority of emotion recognition systems are using a dimensional system. However, systems targeting emotion in a specific context use categorical models more often.

As emotion is the predominant affect category in the sampled papers, the analysis of dimensions and categories focuses solely on that category. The full results can be found in Appendix D.2. Figure 3 presents how often each dimensional ARSs was used The most popular model is VA, in particular the H/L approach. For categorical ARSs the most popular representation is *positive, negative, (neutral)*. Unsurprisingly, these results are not much different from the overall results.

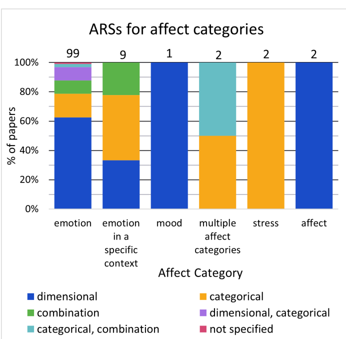

Figure 2: Types of ARSs for different Affect Categories.

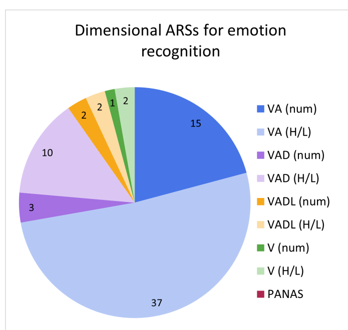

Figure 3: Types of dimensional ARSs for PAAR for emotion

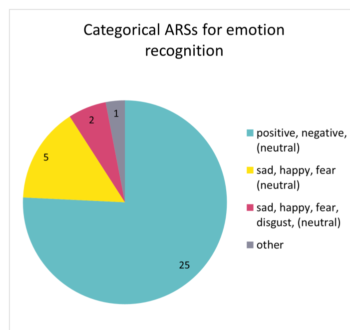

Figure 4: Types of categorical ARSs for PAAR for emotion

3.7 ARSs over time

The popularity of ARSs in PAAR over time aims to detect trends or patterns. Figure 5 presents the results for the types of ARS. In the considered time there were no significant differences between the year, only a small deviation in 2021. The results for dimensional models are presented in more detail in Figure 6. In the last two years, V and VADL models have become less popular. Similarly, the High/Low approaches have been utilized more often in the more recent years. The categorical ARSs are presented in Figure 7. In 2020 and 2021 *positive, negative, (neutral)* was the most common categorical ARS. Since 2022, many papers have utilized one of the other two approaches. It has to be noted that SEED-V, which applies the *sad, happy, fear, disgust, neutral* representation has only been published in 2021.

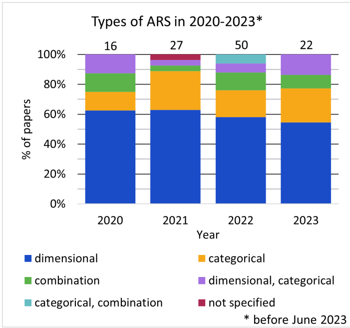

Figure 5: Types of ARSs in PAAR in years 2020-2023 (before June)

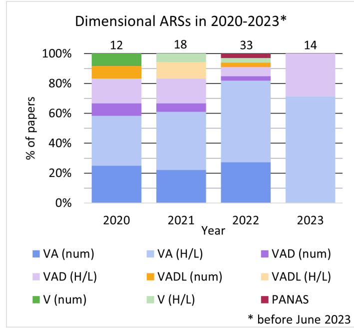

Figure 6: Dimensional ARSs in years 2020-2023 (before June)

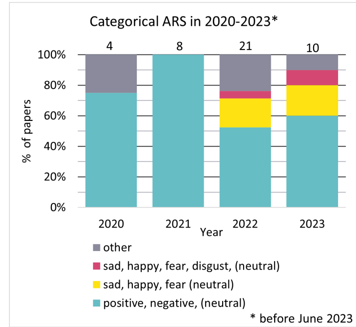

Figure 7: Categorical ARSs in years 2020-2023 (before June)

3.8 Alignment of ARSs with psychological theories

Designing PAAR systems requires researchers to have a background in both psychology and computer science. If a PAAR system uses ARS that is not based on psychology, its applications are limited. Since in this review we only include computer science papers, the authors are assumed to be experts in that field. Therefore, we evaluate whether the ARS was based on actual psychological theories based on the citations. Unfortunately, 66 papers did not mention any psychological work on affect. The remaining papers mention publications of well-known authors. A summary of these authors and the papers that mention their work is presented in Table 11.

Table 11: Most frequently cited authors of psychological papers in the reviewed papers.

Author	Number of papers	Papers
Russell	22	[18], [19], [22], [28], [39], [43], [49], [54], [55], [58], [61], [65], [68], [69], [76], [85], [90], [100], [103], [105], [108], [118], [122], [125]
Ekman	15	[35], [49], [65], [75], [76], [85], [91], [93], [101], [103], [107], [111], [114], [125], [128], [131]
Verma	3	[44], [92], [93]
Parrot	3	[65], [118], [125]
Mehrabian	3	[49], [76], [107]
Plutchik	3	[91], [103], [125]

3.9 Input signals and ARS

The last research question concerns the popularity of ARSs among different input signals. Figure 8 presents how often each type of ARS was used for the most common input signals. For the most popular signals (EEG, GSR, ECG, Respiration), the results are similar to the overall results. The results for less popular signals differ. However, due to the low number of papers, it is not possible to conclude if the ARSs used for these signals deviate from the general results.

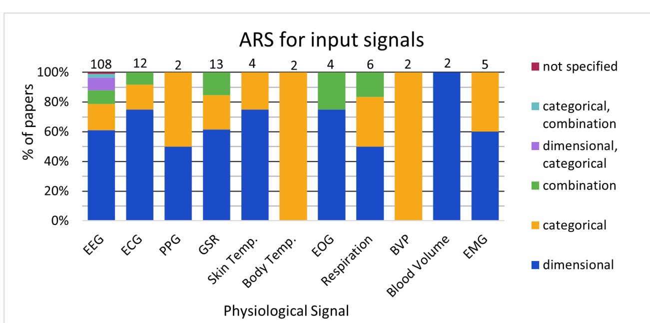

Figure 8: ARSs for different physiological input signals in the reviewed papers.

4 Responsible Research

It is important to consider the universality and reliability of the research. Firstly, we discuss the implications of the SLR being performed by one researcher. Then we reason about the reproducibility of results.

Risk of bias

This review is performed by one Computer Science bachelor student, which imposes a number of risks. Typically, SRLs are done by multiple researchers to reduce bias and errors. Having a single reviewer might cause mistakes in the paper selection and data extraction phases. To prevent this in the methodology we try to standardize these phases as much as possible. However, the complete elimination of this problem is not achievable. Another issue that arises is the lack of psychological knowledge. To answer the research questions and interpret the results properly the reviewer should have enough background in both Computer Science and psychology. To resolve this issue before the review we have filled in this gap and base the answers on appropriate papers. For example, in SQ7 about alignment with psychological theories, the results give the most often cited psychologists. We do not attempt to evaluate the correctness of the ARSs used in PAAR but rather their correlation with the works of affect experts.

Reproduciblity of the results

To verify the results of this review the full procedure can be reapplied. We described the methodology using the PRISMA guidelines, Therefore, we included all the necessary information to repeat the search procedure. We defined eligibility criteria for excluding irrelevant papers and the list of information to be extracted from every paper. The number of papers at every stage of the filtering is also reported. All papers included were cited and included in the bibliography. We acknowledge that SLR performed by one inexperienced researcher in such a short timeframe can lead to errors and misconduct. However, by using standard practices and the help of automated tools for data analysis we try to minimize that risk. For example, most of the tables presented in the Results section were generated automatically and the researcher only verified their correctness.

5 Discussion

This section summarizes the findings of the review and the answers to the SQs. Before discussing the results it is necessary to reason about the possible impact of the feasibility constraints, which is done in section 5.1. Then we can move on to reviewing the results in section 5.2

5.1 Possible impact of feasibility constraints

The first introduced feasibility constraint was narrowing down the timeframe for paper publications. This also limits the answer we can give to SQ6 about the popularity of schemes over time. Moreover, it introduces additional challenges in identifying trends and tendencies. However, we can still give a satisfying answer only for this period that can be used for a full review.

The second adjustment, the dataset filter, has a stronger impact on the results. Authors have to use the same input signals to be able to test the system on a specific dataset. However, it is not required to use exactly the same set of signals as the dataset. For example, many papers used DEEP and SEED and only considered EEG. The dataset might also limit the ARS of PAAR systems, but it does not enforce it completely. Again, a good example is papers using DEAP dataset that ignore the Dominance and Liking (and sometimes even Arousal) dimensions and use the reduced representations. Authors can also decide to transform the ARS used in the dataset into the one of their choice using for example the circumplex model. Therefore, the authors are not forced to use exactly the same ARS as the dataset.

5.2 Results discussion

The information extracted from the papers has sufficed to give answers to all SQs, however, some of them were limited by the lack of representation in the set of sampled papers. The dominating group of systems was EEG-based emotion recognition therefore it is not possible to derive any meaningful conclusions about other input signals and affect categories. Overall, the most common ARSs were the dimensional VA, VAD, and categorical *positive, negative, (neutral)* models. In terms of input signals, we can distinguish 2 main approaches taken in the reviewed papers: only EEG, or multiple signals. For the most frequent signals, the analysis of ARSs type did not reveal if there is any impact the input signals have on the choice of ARS.

There are two most common ways in which authors can account for datasets using different ARSs. One of the options is to use multiple classifications and perform experiments in different settings. Another solution is to translate the ARSs of the dataset into the desired one. However, this might not always be possible and should be done based on psychological works to ensure correctness. This can influence the accuracy results of the experiments. For example, achieving high accuracy when predicting whether Arousal and Valence are high or low is much easier than when predicting their numerical values. Therefore, systems should only be compared against solutions that applied the same modifications to the dataset's ARS. This topic can be further explored by investigating the impact ARS modifications have on accuracy as an extension of this research.

The overall results presented in table 10 show that the categorical ARSs in PAAR are standardized by SEED [135], [136], SEED-IV [137], and SEED-V [138] datasets. This would contradict the claim by [153] [7] that categorical ARSs in PAAR are usually self-made. However, considering the impact of the dataset feasibility filter, it is possible that papers with custom categorical ARSs have been excluded. Therefore, we cannot disprove that claim and leave this question for the full review. However, we can notice that recently published SEED-V [138] considers more categories, and together with SEED-IV [137] they have been gaining popularity in the last two years at the cost of SEED [135], [136]. This could mean that authors prefer representations with more than 3 categories. This trend has to be observed in the next years to confirm if that is the case.

Unfortunately, the reviewed papers do not motivate the choice of ARS extensively. The most common arguments are popularity, simplicity, or the dataset. Over half of the papers do not even refer to psychological theories. This can be caused by the neglect of the importance of the ARS and the role of psychology in PAAR. The reliability of papers that do not properly motivate such a fundamental element of the system can be easily questioned which lowers the scientific value of the paper and the PAAR system. Therefore, authors should pay more attention to this subject in the future.

6 Conclusions and Future Work

In this paper, we have perform an SLR of what ARSs are used in PAAR systems. We explore the type of input signals, affect categories, popularity, and motivations for ARSs. This review also attempts to find a correlation between ARS and time, input signal, or target affective category.

According to the SLR methodology firstly, we have developed a procedure for generating and assessing eligible papers. For feasibility, the review was limited to papers published between 2020 and June 2023 and using at least one of the chosen datasets. The procedure for generating eligible papers can be reused without the additional filters to perform a complete review. The full survey could utilize the results presented in section 3 and exclude the records considered in this paper.

The majority of reviewed papers presented an EEG-based emotion recognition system. Based on the gathered information there is no evidence that there is a significant correlation between ARS and different input signals. Authors often decide to modify the ARS used in the dataset. Our advice is to base this transformation on psychological theories and only compare the results of experiments with papers that perform the same modification. Whether that is the case in the existing papers is left as a future extension for the review. Dimensional ARSs, in particular, High/Low adaptations of VA and VAD are dominating the ARSs used in PAAR. The High/Low approaches have also become more popular in the last two years. Categorical ARSs are usually taken directly from the dataset, however, it is possible this result is an effect of applying the dataset feasibility constraint. The background information and motivations for ARS are often lacking, which has a negative impact on the reliability of the paper.

Although we have managed to give an answer to all research questions the results are not valuable without discussing the limitations. The additional constraints for feasibility had a significant impact on the results. However, some datasets adapt an ARS that can be transformed or reduced into different ARS. Therefore, authors that use these datasets still have some freedom to use the ARS of their choice. As the majority of reviewed papers concerned EEG-based emotion recognition systems, it is not possible to give a certain answer to some of the questions for the less popular input signals and affect categories. We hope that a complete review would be able to do that.

In the future, this review can be continued by removing feasibility filters. Moreover, the datasets and their correlation with ARS can be explored further. For example, it would be interesting to explore how many papers use the same ARS as the dataset, and how many reduce it or apply modification. The analysis of the alignment with psychological theories can be continued by exploring what papers exactly are cited the most often. Lastly, the survey can be complemented by including more systems targeting affect categories different than emotion and using different input signals. This would allow drawing conclusions about these systems and therefore provide more extensive answers to SQ5 and SQ8.

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Appendix

A Constructed queries for the full survey

A.1 IEEE Xplore

("All Metadata":"affect*" OR "All Metadata":"emotion*" OR "All Metadata":"mood" OR "All Metadata":"mental state" OR "All Metadata":"happy" OR "All Metadata":"anger" OR "All Metadata":"sad" OR "All Metadata":"disgust" OR "All Metadata":"fear" OR "All Metadata":"arousal" OR "All Metadata":"valence" OR "All Metadata":"dominance" OR "All Metadata":"stress") AND ("All Metadata":"recogni*" OR "All Metadata":"predict*" OR "All Metadata":"detect*" OR "All Metadata":"classif*") AND ("All Metadata":"physiolog*" OR "All Metadata":{emg} OR "All Metadata":"electromyograph*" OR "All Metadata":{gsr} OR "All Metadata":"glavic" OR "All Metadata":{ecg} "electrocardiogram" OR "All Metadata":{eeg} OR "All Metadata":"electroencephalogram" OR "All Metadata":"cardiovascular" OR "All Metadata":"respirat*" OR "All Metadata":"bio-signal" OR "All Metadata":"biosensor*") NOT ("Document Title":"review" OR "Document Title":"survey" OR "Document Title":"compar*")

A.2 Scopus

(TITLE-ABS-KEY ("affect*" OR "emotion*" OR "mood" OR "mental state" OR "happy" OR "anger" OR "sad" OR "disgust" OR "fear" OR "arousal" OR "valence" OR "dominance") AND TITLE-ABS-KEY ("recogni*" OR "predict*" OR "detect*" OR "classif*") AND TITLE-ABS-KEY ("physiolog*" OR {emg} OR "electromyograph*" OR {gsr} OR "glavic" OR {ecg} "electrocardiogram" OR {eeg} OR "electroencephalogram" OR "cardiovascular" OR "respirat*" OR "bio-signal" OR "biosensor*") AND NOT TITLE-ABS-KEY ("review" OR "survey" OR "compar*")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "ch")) AND (LIMIT-TO (SUBJAREA , "COMP")) AND (LIMIT-TO (LANGUAGE , "English"))

A.3 Web Of Science

((((TS=("affect*" OR "emotion*" OR "mood" OR "mental state" OR "happy" OR "anger" OR "sad" OR "disgust" OR "fear" OR "arousal" OR "valence" OR "dominance")) AND TS=("recogni*" OR "predict*" OR "detect*" OR "classif*")) AND TS=("physiolog*" OR {emg} OR "electromyograph*" OR {gsr} OR "glavic" OR {ecg} "electrocardiogram" OR {eeg} OR "electroencephalogram" OR "cardiovascular" OR "respirat*" OR "bio-signal" OR "biosensor*")) NOT TI=("review" OR "survey" OR "compar*"))

A.4 ACM Digital Library

[[Abstract: "affect*"] OR [Abstract: "emotion*"] OR [Abstract: "mood"] OR [Abstract: "mental state"] OR [Abstract: "happy"] OR [Abstract: "anger"] OR [Abstract: "sad"] OR [Abstract: "disgust"] OR [Abstract: "fear"] OR [Abstract: "arousal"] OR [Abstract: "valence"] OR [Abstract: "dominance"]] AND [[Abstract: "recogni*"] OR [Abstract: "predict*"] OR [Abstract: "detect*"] OR [Abstract: "classif*"]] AND [[Full Text: "physiolog*"] OR [Full Text: {emg}] OR [Full Text: "electromyograph*"] OR [Full Text: {gsr}] OR [Full Text: "glavic"] OR [Full Text: {ecg} "electrocardiogram"] OR [Full Text: {eeg}] OR [Full Text: "electroencephalogram"] OR [Full Text: "cardiovascular"] OR [Full Text: "respirat*"] OR [Full Text: "bio-signal"] OR [Full Text: "biosensor*"]] AND NOT [[Title: "review"] OR [Title: "survey"] OR [Title: "compar*"]]

B Constructed queries with the feasibility filters

B.1 IEEE Xplore

("All Metadata":"affect*" OR "All Metadata":"emotion*" OR "All Metadata":"mood" OR "All Metadata":"mental state" OR "All Metadata":"happy" OR "All Metadata":"anger" OR "All Metadata":"sad" OR "All Metadata":"disgust" OR "All Metadata":"fear" OR "All Metadata":"arousal" OR "All Metadata":"valence" OR "All Metadata":"dominance" OR "All Metadata":"stress") AND ("All Metadata":"recogni*" OR "All Metadata":"predict*" OR "All Metadata":"detect*" OR "All Metadata":"classif*") AND ("All Metadata":"physiolog*" OR "All Metadata":{emg} OR "All Metadata":"electromyograph*" OR "All Metadata":{gsr} OR "All Metadata":"glavic" OR "All Metadata":{ecg} "electrocardiogram" OR "All Metadata":{eeg} OR "All Metadata":"electroencephalogram" OR "All Metadata":"cardiovascular" OR "All Metadata":"respirat*" OR "All Metadata":"bio-signal" OR "All Metadata":"biosensor*") AND ("All Metadata":“DEAP” OR "All Metadata":“AMIGOS” OR "All Metadata":“ASCERTAIN” OR "All Metadata":“BIO-VID_EMO DB” OR "All Metadata":“DREAMER” OR "All Metadata":“MAHNOB-HCI” OR "All Metadata":“MPED” OR "All Metadata":“SEED” OR "All Metadata":“Eight-Emotion” OR "All Metadata":“DECAF” OR "All Metadata":“USI_Laughs” OR "All Metadata":“Driver” OR "All Metadata":“Non-EEG” OR "All Metadata":“Distracted Driving” OR "All Metadata":“WESAD”) NOT ("Document Title":"review" OR "Document Title":"survey" OR "Document Title":"compar*")

B.2 Scopus

(TITLE-ABS-KEY ("affect*" OR "emotion*" OR "mood" OR "mental state" OR "happy" OR "anger" OR "sad" OR "disgust" OR "fear" OR "arousal" OR "valence" OR "dominance") AND TITLE-ABS-KEY ("recogni*" OR "predict*" OR "detect*" OR "classif*") AND TITLE-ABS-KEY ("physiolog*" OR {emg} OR "electromyograph*" OR {gsr} OR "glavic" OR {ecg} "electrocardiogram" OR {eeg} OR "electroencephalogram" OR "cardiovascular" OR "respirat*" OR "bio-signal" OR "biosensor*") AND TITLE-ABS-KEY ("DEAP" OR "Eight-Emotion" OR "MAHNOB" OR "DECAF" OR "ASCERTAIN" OR "USI_Laughs" OR "Non-EEG" OR "Distracted Driving" OR "WESAD" OR "DREAMER" OR "MPED" OR "SEED" OR "BIO-VID_EMO") AND NOT TITLE-ABS-KEY ("review" OR "survey" OR "compar*")) AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020)) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "ch")) AND (LIMIT-TO (SUBJAREA , "COMP")) AND (LIMIT-TO (LANGUAGE , "English"))

B.3 Web Of Science

((((TS=("affect*" OR "emotion*" OR "mood" OR "mental state" OR "happy" OR "anger" OR "sad" OR "disgust" OR "fear" OR "arousal" OR "valence" OR "dominance")) AND TS=("recogni*" OR "predict*" OR "detect*" OR "classif*")) AND TS=("physiolog*" OR {emg} OR "electromyograph*" OR {gsr} OR "glavic" OR {ecg} "electrocardiogram" OR {eeg} OR "electroencephalogram" OR "cardiovascular" OR "respirat*" OR "bio-signal" OR "biosensor*")) NOT TI=("review" OR "survey" OR "compar*")) AND TS=(“DEAP” OR “AMIGOS” OR “ASCERTAIN” OR “BIO-VID_EMO DB” OR “DREAMER” OR “MAHNOB-HCI” OR “MPED” OR “SEED” OR “Eight-Emotion” OR “DECAF” OR “USI_Laughs” OR “Driver” OR “Non-EEG” OR “Distracted Driving” OR “WESAD”)

B.4 ACM Digital Library

[[Abstract: "affect*"] OR [Abstract: "emotion*"] OR [Abstract: "mood"] OR [Abstract: "mental state"] OR [Abstract: "happy"] OR [Abstract: "anger"] OR [Abstract: "sad"] OR [Abstract: "disgust"] OR [Abstract: "fear"] OR [Abstract: "arousal"] OR [Abstract: "valence"] OR [Abstract: "dominance"]] AND [[Abstract: "recogni*"] OR [Abstract: "predict*"] OR [Abstract: "detect*"] OR [Abstract: "classif*"]] AND [[Full Text: "physiolog*"] OR [Full Text: {emg}] OR [Full Text: "electromyograph*"] OR [Full Text: {gsr}] OR [Full Text: "glavic"] OR [Full Text: {ecg} "electrocardiogram"] OR [Full Text: {eeg}] OR [Full Text: "electroencephalogram"] OR [Full Text: "cardiovascular"] OR [Full Text: "respirat*"] OR [Full Text: "bio-signal"] OR [Full Text: "biosensor*"]] AND [[Full Text: "deap"] OR [Full Text: "amigos"] OR [Full Text: "ascertain"] OR [Full Text: "bio-vid_emo db"] OR [Full Text: "dreamer"] OR [Full Text: "mahnob-hci"] OR [Full Text: "mped"] OR [Full Text: "seed"] OR [Full Text: "eight-emotion"] OR [Full Text: "decaf"] OR [Full Text: "usi_laughs"] OR [Full Text: "driver"] OR [Full Text: "non-eeg"] OR [Full Text: "distracted driving"] OR [Full Text: "wesad"]] AND NOT [[Title: "review"] OR [Title: "survey"] OR [Title: "compar*"]] AND [E-Publication Date: (01/01/2020 TO 12/31/2023)]

C Search results

Table 12: The effect of applying the feasibility constraints has on the number of search results from the included databases.

Query	Web of Science	ACM DL	IEEE Xplore	Scopus
full review query	4828	123	7980	1311
only year of pub. constraint	1911	52	2893	494
only dataset constraint	542	31	785	108
both constraints	**310**	**13**	**410**	**53**

D Results

D.1 Datasets

Datasets	Number of papers
DEAP	46
SEED	12
DEAP, DREAMER	10
DEAP, SEED	9
DEAP, MAHNOB-HCI	6
SEED, SEED-IV	3
WESAD	3
DREAMER	2
AMIGOS	2
DREAMER, AMIGOS	2
DEAP, DREAMER, DASPS	2
AMIGOS, DREAMER	1
DEAP, MAHNOB-HCI, Eight-Emotion (set B)	1
SWEL, AMIGOS	1
SEED, DREAMER	1
SEED-V	1
SEED, MPED, SDEA, DREAMER	1
SEED-IV, SEED-V	1
DEAP, SEED, SEED-IV	1
DEAP, SEED, AMIGOS	1
DREAMER, GAMEEMO	1
SEED-IV	1
DEAP, MAHNOB-HCI, SEED	1
ASCERTAIN	1
DEAP, MAHNOB-HCI	1
DEAP, AMIGOS	1
DEAP, DREAMER, DESC	1
AMIGOS, SEED-IV, PD, HC (datasets for Parkinson's disease)	1
AMIGOS	1
total	**115**

Table 13: An overview of datasets used in papers included in the review

D.2 ARSs for different affect categories

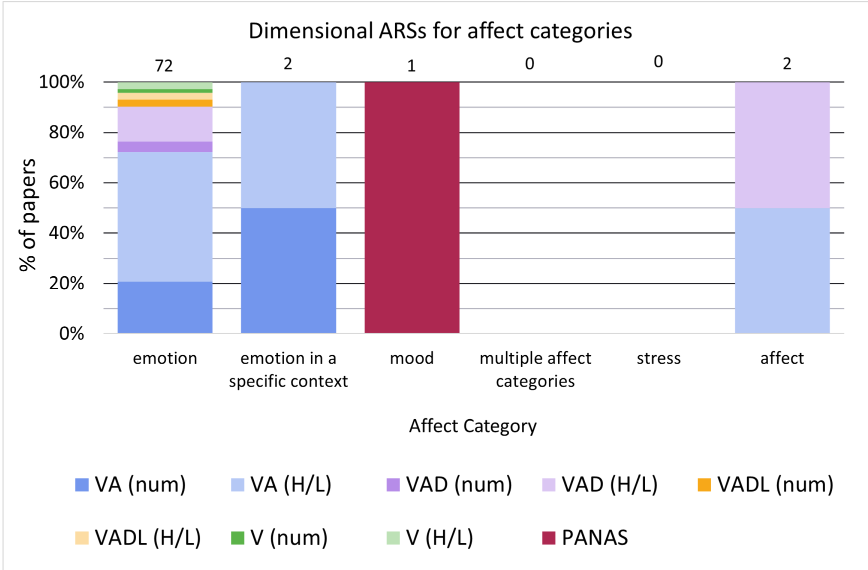

Figure 9: Dimensional ARSs for affect categories

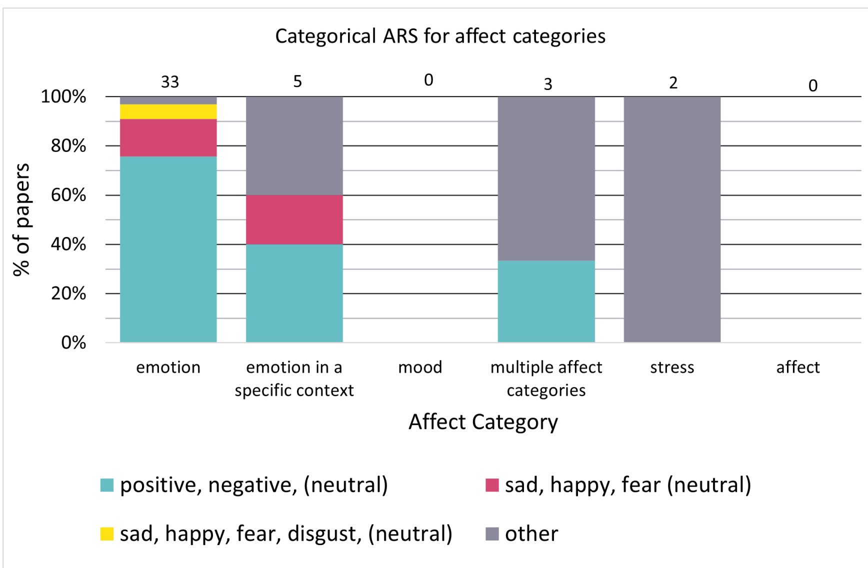

Figure 10: Categorical ARSs for affect categories