Subjectivity in Emotional Perception

Systematic Review on the Influence of Perceiver Characteristics

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Abstract

While emotional recognition is a fundamental social skill, individuals often interpret the same emotional expression differently. Previous research has shown that the interpretation of emotional expressions depends strongly on contextual information, yet the role of the perceiver's internal context remains less clearly understood. This study investigates which psychological and cognitive characteristics of human perceivers influence the understanding of others' emotions through audio-visual stimuli. A systematic literature review was conducted to collect findings from experimental studies. A synthesis of 30 experiments indicates that emotional competence and several cognitive characteristics predict greater emotion recognition accuracy. Meanwhile, personality traits and emotional states introduce subjectivity in the forms of background-scene susceptibility, emotional distortions where an individual perceives a feeling absent from the stimulus, and projections where observers attribute their own current feelings or past experiences onto others' expressions.

1 Introduction

Emotional expression is a principal component of social interactions. Facial and bodily expressions, as well as vocal cues, are non-verbal pathways for communicating meaningful emotional information [56]. Nonetheless, emotional signals are often ambiguous in everyday life [67], and decoding them is dependent on the interpretation of the perceiver, who can introduce personal biases [72]. This is particularly evident for facial muscle configurations, which are inherently ambiguous and can support multiple interpretations depending on the context [37]. Researchers argue against the common assumption that emotions can be objectively inferred from faces [5].

This study reviews the sources of subjective interpretation of audio-visual emotional stimuli. The aim is to better understand which characteristics of an individual, in terms of psychology and cognition, contribute to variability in the perception of emotional expressions. This is done through a systematic collection of previous literature and a synthesis of experimental findings.

The motivation behind examining these perceiver characteristics arises from the field of affective computing. Nowadays, new technologies take on the task of automatic emotion recognition, with applications in healthcare, psychology, surveillance and decision-making [34, 32, 9]. The deployment of such technologies has prompted ethical concerns, particularly regarding potential biases in AI systems and the protection of individual privacy [19].

A review on these challenges found that facial emotion recognition systems show considerable unreliability in their performance, with error rates that vary across different racial and demographic groups [50]. In addition, they are typically trained using limited datasets that may include annotation bias [50]. Since these datasets are commonly labeled through online crowdsourcing [44], individual differences among annotators may influence the resulting emotion labels.

Models trained on subjective data have a higher probability of producing and amplifying unjust outcomes [68]. For this reason, understanding the subjectivity underlying human emotional perception can help identify potential sources of bias in emotion recognition technologies trained on human-annotated data. While subjectivity in emotional perception is unavoidable [5], certain forms of bias can become problematic when they lead to systematic discrimination [4, 53]. Recognizing these limitations is important, as such technologies are increasingly being considered for use in high-stakes settings, including workplaces and law enforcement [9, 41].

Following this Introduction, Section 1 further explores Background and Related Work. The Research Question is specified in Section 2. The Methodology of the systematic literature review is explained in Section 3. The Results are presented in Section 4, followed by Responsible Research in Section 5. The report ends with the Discussion in Section 6, which includes Limitations, Quality Assessment of the Literature and Future Work suggestions.

1.1 Background

Previous research has emphasized the importance of context during emotional recognition [35]. Barrett et al. demonstrate that context significantly shapes the assignment of meaning to audio-visual emotion expressions [6]. When humans try to understand what another person feels, they process contextual information to adopt the other's perspective [39].

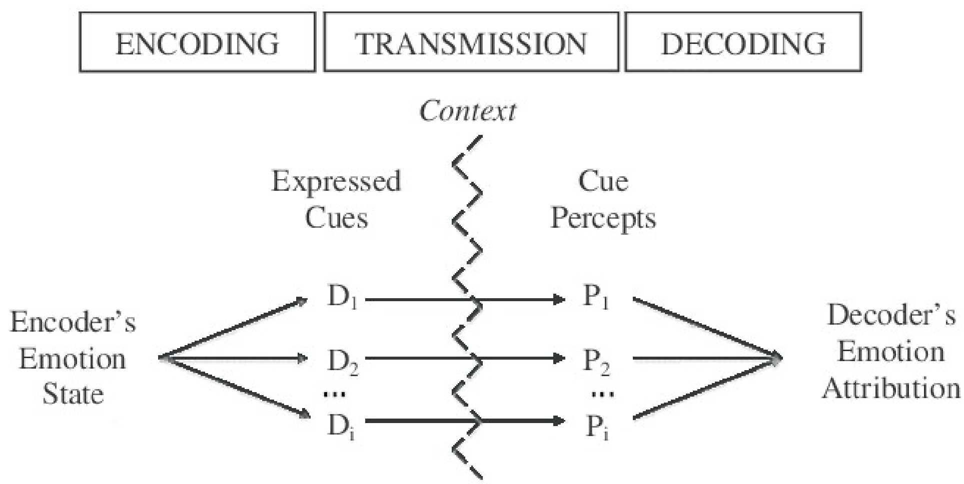

Figure 1: Modified form of Brunswikian lens model of the process of emotional expression and perception. The figure is adapted from Scherer et al. on "Vocal Expression of Emotion" [66], this figure was simplified for the present paper.

Dudzik et al. highlight that this process should be adopted by automatic affect recognition systems to improve their performance [22]. In their paper, they review audiovisual databases for the inclusion of contextual information. For this, the Modified Brunswikian Lens Model is used as a theoretical framework of how context is an inseparable component of emotional transmission. Similarly, Scherer uses this model in a review of research paradigms focused on vocal communication of emotion [65]. A simplified version of the model is presented in Figure 1.

The model describes emotion perception as a three-stage process: the encoding of emotions into observable cues, the interpretation of these cues through contextual information, and the subsequent attribution of emotional meaning by the perceiver. The results of Dudzik et al. show that while context regarding the encoding and transmission of emotions is included in databases, there is little information regarding perceiver-related context. The limited available information is mainly represented through demographic categories. Engelmann et al. (2013) point out that the underlying cognitive mechanisms of demographic differentiation have received relatively little attention [24].

In order to better understand the internal context of the perceiver from perspectives beyond group-based categories, this research explores cognitive and psychological factors. This may help clarify which additional variables on the perceiver's side interact with emotional cues during the decoding of emotional expressions, and how these factors influence the attribution of emotional meaning.

1.2 Related Work

There are previous literature reviews that examine the impact of perceiver characteristics. However, because they focus on specific constructs in isolation, they do not provide a unified synthesis of the broader set of psychological and cognitive characteristics that may influence emotional perception.

Some emotional competence traits have been previously reviewed, in specific empathy and alexithymia. In "In the Eyes of the Beholder: How Empathy Influences Emotion Perception", Chakrabarti et al. review empirical evidence showing that trait empathy is associated with variability in emotion recognition and neural processing of emotional stimuli [14]. Another systematic review focused on alexithymia, and a meta-analysis of 24 studies showed a moderate negative association between non-clinical alexithymia traits and static facial expression recognition [75].

Personality-related influences have been synthesized by Furnes et al. Their review of facial and vocal emotion recognition studies shows mixed and often contradictory results regarding the relationship between Big Five personality traits and emotion recognition accuracy [29]. Similarly, a review by Rusting finds no consistent direct correlation between personality characteristics and emotional processing. Instead, the review argues that variability in emotional processing is better explained through integrative frameworks in which stable personality traits interact with transient mood states [62].

Cognitive individual differences have also been addressed. Adolphs reviews neurological studies related to emotion recognition. When reporting on the neural pathways underlying emotional perception he emphasizes the role of attentional and perceptual processes in decoding emotional facial expressions [1]. Similarly, Pessoa's essay "On the relationship between emotion and cognition" reviews how cognitive control and attention interact with emotional processing systems. He suggests that executive functions modulate the perception and interpretation of emotional stimuli [57]. Both of these reviews primarily focus on a neuroscientific perspective.

From this literature, it is clear that the influence of individual differences on emotional perception is complex. The current research appears fragmented across affective science, personality psychology, and cognitive neuroscience. This complicates efforts to draw overarching conclusions about which individual differences are most relevant regarding their influence on emotional perception. This review seeks to fill that gap by combining evidence from various psychological and cognitive experiments linked to emotion recognition. The goal is to offer a more unified understanding of which characteristics contribute to subjectivity.

2 Research Questions

This research is based on the following research question:

"How do psychological and cognitive characteristics of the perceiver shape audio-visual emotion perception?"

To address this overarching question, two sub-questions are examined:

RQ1: "Which perceiver characteristics are correlated with accuracy in audio-visual emotion recognition?"

RQ2: "How do perceiver characteristics contribute to subjective differences in emotional perception beyond recognition accuracy?"

A perceiver in this context is a human who receives and interprets emotional stimuli. This individual is the observer of another person's emotional expression and is responsible for attributing meaning to it by understanding which emotions the other person is experiencing.

This study focuses exclusively on audio-visual emotion recognition. Audio-visual emotional stimuli can include images or video and voice recordings which capture facial, bodily and voice expressions. By narrowing the scope to audio-visual modalities, the research becomes more manageable given the time limitations. The restriction excludes text and word-based emotion recognition, which fall within the domain of linguistics.

The term "individual characteristics" refers to internal psychological or cognitive attributes that might influence the interpretation of emotional cues. These could be stable traits of the perceiver, such as personality traits [17], or they could be temporary states during emotion recognition tasks, for example emotional states [27]. Group categories like demographics are not considered here. Characteristics related to medical or psychological conditions are also excluded. This is done to keep the scope of the research narrow enough for timely completion.

3 Methodology

This study was completed as a systematic literature review. The purpose of a literature review is to collect the most relevant evidence to informatively address the research question [8]. What makes a review systematic is the transparent planning and documentation of the process. This method was chosen because it allows the integration of findings from different study designs, thereby capturing different forms of subjectivity across studies. This would not be feasible by conducting a primary research study instead, as it would be difficult to measure a wide range of outcomes within one coherent study design [18].

The report follows the PRISMA 2020 guidelines, which are specifically designed to guide the reporting of systematic reviews [55]. These guidelines specify the items that should be included in a systematic review, such as the criteria used for selecting the literature. Adhering to this standard improves transparency in the reporting process [70].

The bibliographic management software that supported this study was Zotero [71]. It was used for the collection and organization of the initial set of papers and their metadata. Afterwards, it supported systematic tagging during the screening process, and enabled the export of references in BibTeX format.

3.1 Search Strategy

Scopus was chosen as the primary database due to its extensive coverage of empirical research papers [12]. It includes a wide range of fields, making it well suited for interdisciplinary research on emotion perception and individual differences.

PsycInfo was included as a secondary source of literature due to its strong focus on psychological research [15]. As a subject-specific database, PsycInfo typically yields fewer but more highly relevant results within the field of psychology. In contrast to broader

Table 1: Synonyms of search terms.

Emotion	**Perception**	**Individual characteristics**	**Influence**
emotion*	perception	individual characteristics	influence*
feeling*	perceive*	individual differences	bias*
mood*	understand*	individual traits	modulat*
reaction*	recogni*	perceiver traits	determin*
affect*		perceiver differences	effect
		perceiver characteristics	affect*
		perceiver context	
		subjectivity	

multidisciplinary databases, PsycInfo was expected to contribute complementary studies that are explicitly grounded in psychological experimental research on emotion perception and individual differences. This allows for a more focused retrieval of complementary studies that may not be prioritized in larger databases.

Google Scholar was considered as an alternative database but was not included in the search strategy. Although it provides broad coverage of scholarly literature, it does not offer an efficient way to export large numbers of records to bibliographic software [7], which is particularly important during the initial screening phase. Given the time constraints of this review, Scopus and PsycInfo, were considered more practical.

A scoping search took place to identify key search terms: Emotion, Perception, Individual characteristics and Influence. These defined the scope of the research question and formed a base for query development. Table 1 shows synonyms of the query terms which were joined with OR, while the terms where all joined with AND operators. The query was tried on Scopus and went through iterative evaluation until it produced limited and relevant results as shown in Appendix A. Then, the query was adapted to fit the PsycINFO database.

Studies were targeted through explicit Inclusion Criteria, to ensure their relevancy to answering the research question. These prerequisites are presented in Table 2.

Table 2: Inclusion Criteria

No	**Inclusion Criterion**
I-1	The paper discusses at least one psychological or cognitive individual characteristic and explores its influence on emotional perception.
I-2	The paper includes experimental findings on the influence that characteristic has.
I-3	The experiment tests effect on emotional perception based on audio-visual stimuli.

3.2 Literature Screening

A total of 119 papers were collected from both databases. The initial set of papers underwent Title, then Abstract and lastly Full Text screening. Through these stages, papers were assessed for their relevancy. Exclusion Criteria were used to inform this classification. These explain the different reasons for exclusion and can be viewed in Table 3.

Table 3: Exclusion Criteria

No	Exclusion Criterion	Motivation
E-1	Study on automatic emotional recognition or other machine learning models	Provide no insight on human-perceiver characteristics.
E-2	Review Paper	Preference for first-hand evidence so that the results do not depend on other people's interpretations.
E-3	Focus on clinical populations, meaning research involving mental or medical disorders	Some disorders affect emotional perception [43]. This will be excluded to keep the scope narrow.
E-4	Emotion recognition through text or words	The current scope is narrowed to audiovisual emotional recognition.
E-5	Study on the effects of emotion perception on other processes	It does not investigate determinants of emotion perception.
E-6	Study on the perception of non-emotional information	Not relevant to the research question.
E-7	Study involves no emotion perception tasks.	Provides no insights on emotional perception.
E-8	All the characteristics studied were not psychological or cognitive. Some examples are demographic characteristics and language proficiency	The current scope is narrowed to psychological and cognitive determinants.
E-9	Individual differences were induced through prescribed medications	Not relevant to standard subjectivity of emotional perception.

A PRISMA Data Flow Diagram was used to report on the exclusion of papers during each stage as presented in Figure 2. The diagram provides a transparent overview of how papers progressed through each screening phase, leading to the final set of included papers [60]. In order to improve efficiency, full text reading of 24 papers was performed once, during which screening, data extraction, and quality assessment were conducted.

3.3 Data Extraction

To extract data during the full text reading, an Excel spreadsheet was created. Each row corresponded to a single experiment; therefore, papers reporting multiple experiments required multiple rows. In total, 30 experiments were recorded in the spreadsheet.

The primary focus was on identifying the perceiver characteristics being tested and the resulting findings. Some supplementary information was also extracted. This included participant population, experimental environment, emotional stimuli used, and a description of the emotion recognition task. These data were collected to facilitate the clustering of similar studies during data analysis. The extracted information also supported the quality assessment of the included studies. Notes on study quality were recorded alongside the extracted data.

4 Results

The 30 experiments included in the review were divided into two categories for analysis. First, 17 experiments examined the relationship between perceiver characteristics and emotion recognition accuracy. These investigated whether individuals with different character-

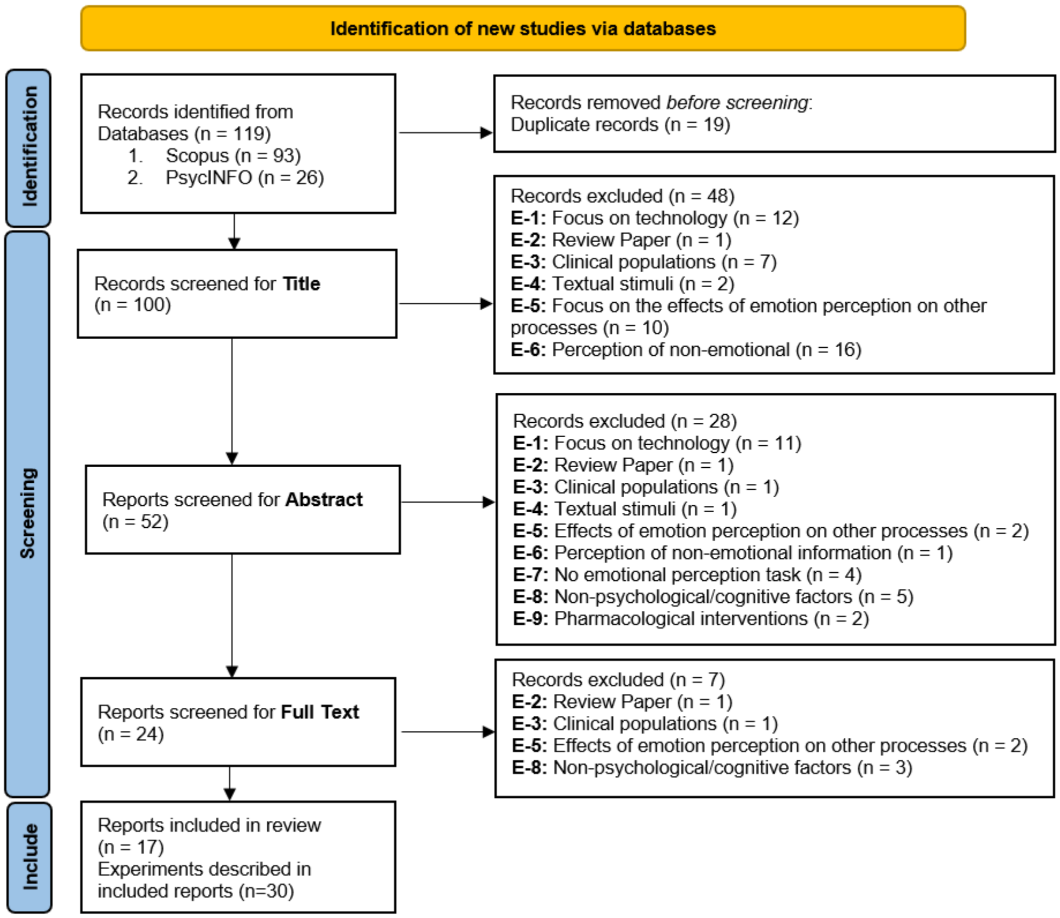

Figure 2: Adapted PRISMA 2020 flow diagram for systematic reviews which included searches of databases and registers only [55]. The right-hand side of the diagram shows the reasons for exclusion at each stage, as well as the number of papers excluded under each criterion.

istics showed higher or lower accuracy in recognising underlying emotional expressions. The remaining 13 experiments investigated other forms of subjectivity in emotion perception.

4.1 Emotional Recognition Accuracy (ERA)

To address RQ1, studies examining ERA were synthesized in Table 4.1. The studies were organized according to the perceiver characteristics, enabling the identification of those that show a consistent direction of influence on ERA.

Table 4: Reported correlations between perceiver characteristics and audio-visual emotion recognition accuracy. Experiment identifiers are provided alongside the citation of the study reporting each correlation. The asterisk (*) denotes that the reported effect is specific to particular emotions.

Perceiver Characteristic	**Positive**	**Negative**	**Null**
Promotion regulatory focus	[64, E1, E2]		
Prevention regulatory focus		[64, E1]	[64, E2]
Emotional self-efficacy	[21, E30]		
Internal feeling richness	[76, E9]		
Emotional intelligence	[45, E22]		
Alexithymia		[16, E16] [45, E22]	
Affective empathy	[54, E12, E15]		[54, E13, E14]
Cognitive empathy	[54, E14, E15]		[54, E12, E13], [45, E22]
General intelligence	[16, E17]		
Facial recognition ability	[76, E9]		
Spontaneous gaze following	[69, E20]		
Openness	[45, E22]	[29, E18]*positive, sad	[31, E10] [29, E18]
Conscientiousness	[29, E18]*neutral		[31, E10] [29, E18] [45, E22]
Agreeableness	[29, E18]*distrust		[31, E10] [29, E18] [45, E22]
Autistic traits		[36, E11]*anger	[36, E11], [16, E16], [45, E22]
Attachment anxiety	[28, E6]	[28, E5]	

Overall, the most consistent positive associations with ERA were found for the domain of emotional competence: the traits of emotional self-efficacy, internal feeling richness and emotional intelligence showed clear positive association with ERA in one experiment each [21, 76, 45].

Emotional self-efficacy concerns an individual's belief regarding how effectively they can regulate their emotions [59]. Next, internal feeling richness refers to the belief that one experiences deep and highly varying emotions, and that emotional experience constitutes an important aspect of life [76]. Lastly, emotional intelligence, as tested by Laukka et al., is the ability to recognize and anticipate the emotional consequences of social and personal situations [45, 48].

This finding is consistent with the negative correlations, reported in two studies, between ERA and alexithymia, a trait characterized by difficulties in emotional processing [47]. Specifically, in this context it was examined as difficulty in understanding and describing one's own emotions, and was not associated with any mental illness symptomatology [16, 45].

Empathy dimensions showed mixed findings, with some experiments finding positive associations with ERA [54], while others, including those conducted by the same research team, found no significant relationship [45, 54]. In the studies, empathy was differentiated into two dimensions. The first, cognitive empathy, referred to the ability to infer another person's emotions [3]. The second, affective empathy, was defined as the ability to personally experience another person's emotions. [49].

Extending to cognitive characteristics, positive associations were found for several measures. Both facial recognition ability and general intelligence were linked to higher emotion recognition accuracy [76, 16]. In addition, spontaneous gaze following was positively associated with ERA [69], referring to the automatic tendency to shift attention in the same direction as another person's gaze.

Further, promotion regulatory focus was positively associated with ERA in two experiments by the same research group [64]. Regulatory focus theory distinguishes between a promotion focus, oriented toward achieving gains and avoiding errors of omission, and a prevention focus, oriented toward avoiding losses and risks [61]. Sassenrath et al. suggested that the effect of promotion focus on ERA may be explained by visual allocation strategies, as promotion focused individuals showed shorter fixations on specific facial regions [64].

Findings for attachment anxiety were mixed and appeared to depend on the amount of emotional information provided [28]. When participants were asked to recognize emotional stimuli as soon as the emotion appeared on a face, individuals high in attachment anxiety terminated the video earlier and showed poorer ERA than those low in attachment anxiety. However, when provided with the same amount of emotional information, individuals high in attachment anxiety reported higher ERA than others.

Personality traits showed some partial associations with ERA, limited to specific emotions, and overall inconsistent effects [45, 29, 31]. Laukka et al. found a positive association for the openness dimension that was not limited to specific emotions [45]. In contrast, Furnes et al. found that openness predicted lower ERA for all positive emotions as well as sadness [29]. According to the Big Five model, openness refers to the extent to which a person is receptive to new experiences and ideas, as well as to creativity [51].

Autistic traits were measured using the Autism Spectrum Quotient (AQ) questionnaire [36, 16, 45]. This questionnaire captures individual differences in autism-related traits, which are thought to be continuously distributed throughout the general population rather than being limited to clinically diagnosed individuals [63]. One experiment found lower accuracy of anger recognition in facial expressions for individuals with high AQ score [36].

4.2 Other Emotion Perception Effects

In order to explore different biases introduced, studies with different measurements of outcomes related to emotional recognition tasks were analyzed. Table 5 summarized the significant effects. Some identified biases are related to background-image susceptibility, others to emotion-specific distortions, and some fall under the category of projection biases. These are explained in the paragraphs below.

Susceptibility to background images was tested using an emotion recognition task in which facial expressions were presented with congruent or incongruent background scenes, and the influence of the background on facial emotion recognition was measured. Extroversion and agreeableness were associated with increased susceptibility to contextual influences during emotion recognition, even though participants were instructed to identify the emotion that best matched the face [25].

Table 5: Reported effects of perceiver characteristics on emotional perception, excluding emotion recognition accuracy. Experiment identifiers are provided alongside the citation of the study reporting each correlation.

Characteristic	**Effect on Emotional Perception**
BIS	Low bg-image susceptibility [46, E8]
BAS	High bg-image susceptibility [46, E8]
Cognitive empathy	Low influence of affective state on emotion perception [74, E7]
Context-influence	Stable individual differences in susceptibility to audio-visual context during facial emotion recognition [25, E24, E26, E27]
Idiosyncratic associations	Decision bias toward emotion associated with similar looking faces from past experience [23, E23]
Spontaneous gaze following	Faster emotional recognition [69, E20]
Extraversion	High bg-image susceptibility [25, E28], more joy distortions [52, E29]
Agreeableness	High bg-image susceptibility [25, E28], more love distortions [52, E29]
Aggression	More anger distortions [52, E29]
Attention Seeking	More love distortions [52, E29]
Distrust	More anger distortions [52, E29]
Criticism Avoidance	More anger distortions [52, E29]
Attachment anxiety	Earlier emotion onset/offset detection [28, E3, E4], Longer fixation on emotional faces [73, E21]
Attachment avoidance	Longer fixation on emotional faces [73, E21]
Current affect	Tendency to project affective state on expressions [74, E7]
Trait anxiety	Shorter fixation on emotional faces [73, E21]
State anxiety	Shorter fixation on emotional faces [73, E21]
Negativity Perception	Less sadness distortions [52, E29]
Loneliness	More disgust and anger distortions [52, E29]
Autonomy Concerns	More fear distortions [52, E29]
Aggression Concerns	More fear distortions [52, E29]

Furthermore, higher behavioral inhibition system (BIS) sensitivity was associated with reduced effects of background-image information, whereas higher behavioral activation system (BAS) sensitivity was associated with stronger effects [46]. BIS reflects sensitivity to punishment and inhibits behavior that may lead to negative or painful outcomes, whereas BAS reflects sensitivity to reward and supports goal-directed behavior [13].

Additionally, Ensenberg et al. found that individuals' susceptibility to background images shows strong stability across experimental sessions [25]. Some participants relied more heavily on facial information, whereas others were more influenced by task-irrelevant contextual cues during face categorization. When facial emotion recognition was combined with vocal emotional stimuli, participants who were susceptible to background images were also similarly influenced by emotional voice cues. Furthermore, this susceptibility was unrelated to global and local perceptual processing styles, basic emotion recognition ability, empathic traits, or analytic versus holistic thinking styles. Overall, Ensenberg et al. suggest that susceptibility to contextual information during emotion perception is a stable individual trait that may extend across multiple sensory modalities.

Miguel et al. explored systematic distortions in emotion perception across individual differences of the perceiver [52]. In their report, a distortion refers to the perception of an emotional expression that is not present in the stimulus. Aggression, distrust, loneliness and avoidance of criticism were associated with increased anger distortions. Loneliness was additionally linked to increased disgust distortions. Concerns regarding aggression and autonomy were associated with greater fear-related distortions.

One bias identified in relation to projection is that perceivers often project their own emotional state onto others [74]. Specifically, an individual's current affective state was associated with a tendency to interpret others' facial expressions in alignment with their own emotions. This effect was especially significant when participants were required to distinguish between angry and fearful faces. Cognitive empathy appeared to mitigate this influence of personal affective states on emotion perception [74].

A study by El Zein et al. found that idiosyncratic face–emotion associations can bias recognition decisions toward emotion-congruent interpretations [23]. This type of projection bias occurs when individuals' personal experiences lead them to associate facial features resembling those of previously encountered people with particular emotions. As a result, similar-looking faces may be interpreted in line with these learned associations rather than solely on the basis of the emotional expression being displayed. The effect remained significant even after controlling for shared associations, suggesting that personal experiences influence associations of faces, beyond societal stereotypes.

Several characteristics influenced attentional processing of emotional information [73, 69]. High attachment anxiety as well as avoidance predicted longer fixation durations on emotional faces [73]. In contrast, trait and state anxiety were associated with shorter fixation times [73]. Spontaneous gaze following was linked to faster emotional recognition [69].

5 Responsible Research

This study was conducted as a systematic literature review and therefore did not involve direct experimentation with human participants, the collection of personal data, or the handling of sensitive information. Nevertheless, it is important to consider the societal implications of the topic.

5.1 Ethics

The findings of this review may be relevant for the development of automatic emotion recognition systems. Such technologies are currently controversial as they introduce privacy concerns and their misuse could potentially enable subtle emotional manipulation of users. Since emotional perception is inherently subjective, systems may reproduce existing perceptual biases. The purpose of this research is not to promote the deployment of emotion recognition technologies, but rather to inform about the sources bias that should be considered when designing, evaluating, and regulating such systems.

5.2 Reproducibility

The review was conducted following the PRISMA 2020 guidelines, and the search strategy is reported in sufficient detail to support replication [55]. In principle, another researcher could repeat the searches in Scopus and PsycINFO and apply the same eligibility criteria to obtain a broadly comparable set of studies.

However, several stages involved subjective decision-making, including the selection of databases, the refinement of search queries, and the interpretation of inclusion and exclusion criteria. In addition, study screening, quality assessment, and data extraction were performed by a single reviewer, which may introduce selection bias and influence the final set of included studies [40].

6 Discussion

In line with the Modified Brunswikian Lens Model, emotional meaning appears to be constructed through an interaction between observed cues and the observer's internal context [11].

To answer RQ1, emotional competence appeared to be the most consistent predictor of emotion recognition accuracy. Emotional richness, intelligence and self-efficacy were positively associated with performance [21, 76, 45], while alexithymia showed negative association [16, 45]. Cognitive and perceptual abilities such as promotion regulatory focus, facial recognition ability, general intelligence, and spontaneous gaze following tendency also increased the accuracy of emotion recognition [64, 16, 76, 69].

To answer RQ2, several characteristics introduced systematic biases in emotion perception. Individuals differed in their susceptibility to contextual information, suggesting that contextual cues are weighted differently across observers [26]. Individual traits, as well as experienced emotions and concerns, were linked to specific emotion distortions [74, 52]. Finally, learned face associations influenced judgments, indicating that perceivers may project their own experiences onto others' expressions [23].

Overall, the findings indicate that emotion recognition should be understood as a process of interpretation rather than simple decoding. These findings also have implications for automatic emotion recognition systems. Most affective computing datasets treat human emotion labels as objective ground truth. However, the current review suggests that these labels are themselves influenced by perceiver characteristics. Consequently, datasets may contain hidden biases originating from the annotators themselves.

6.1 Quality Assessment

The included studies generally employed established scientific methods and reported their procedures. However, several methodological limitations should be considered when interpreting the findings.

First, the majority of perceiver characteristics were measured using self-report questionnaires. Although these instruments are widely used and often validated, they remain vulnerable to biases such as social desirability [30] and inaccurate self-perception [2].

Regarding the experimental setup, 14 of the collected experiments collected data online. Online recruitment may provide advantages, including larger and more diverse samples compared to traditional laboratory studies [33, 10].

The rest of the experiments were parts of laboratory studies, with participants drawn from university populations. This limits their generalizability to the broader public [38]. As a result, the findings cannot be directly applied to annotators of emotional expression data, who may show wider demographic profiles. While this means the current findings should not be viewed as definitive, they still provide insights into real-world variance in emotional perception and annotation.

6.2 Limitations

The most significant limitation faced in this study was the time restriction. In total, 9 weeks were available from the beginning of the research since the report deadline. During these weeks, full-time work on the research was also not possible due to additional academic responsibilities.

Only 119 papers were screened, even though many more surfaced by wider queries as seen in Appendix A. The scope was intentionally limited to psychology and cognitive science perspectives. Other potential sources of subjectivity in emotional perception were excluded, such us demographic categories, neurobiological confounds and symptoms of mental or medical disorders [20, 43, 58].

This focus on cognitive and psychological differences is primarily motivated by Dudzik et al., who found that a perceiver's knowledge, past experiences, perspective-taking abilities, and personality are heavily overlooked in audio-visual emotion recognition datasets [22]. While demographic categories are frequently studied, these deeper cognitive traits represent a critical source of hidden bias in training data. Furthermore, it was argued that psychological traits can be easily evaluated using short, validated, self-report tools, which makes them highly suitable for reliable assessment in time-constrained scenarios, such as the online crowdsourcing environments typically used to label emotion recognition datasets [44].

Neurobiological characteristics were omitted due to the impracticality of requiring specialized medical equipment during data collection. Medical and mental disorders were excluded to focus on understanding standard population variability.

The scope was also limited to audio-visual stimuli. This research was part of a project to explore contextual cues for audio-visual emotion recognition, therefore the study was not extended to other modalities, to maintain the theme.

Another consequence of the time limitation was the exclusion of a meta-analysis for the findings. There was no time for a statistical review, so the results were only descriptively analyzed.

Lastly, a single reviewer conducted the screening and data extraction, introducing potential selection bias. While an explicit set of exclusion criteria was applied to standardize the process, inter-rater variability remains a possibility, and a different reviewer may have selected a slightly different final set of studies [40].

6.3 Future Work

Future research could investigate how psychological and cognitive characteristics may mediate the effects of broader demographic factors, such as culture, gender, and age, on emotion perception [20]. This could be explored through primary research combining demographic measures with questionnaires assessing relevant psychological traits, followed by mediation analyses to determine the extent to which these characteristics explain observed demographic differences.

A neuroscientific perspective may also help explain the mechanisms underlying the effects identified in this review. Future studies could examine whether specific brain regions or functions are associated with the influence of psychological and cognitive traits on emotion perception. Such research could contribute to a deeper understanding of why individuals differ in their interpretation of emotional expressions.

Finally, future work could involve the systematic analysis of existing emotion recognition datasets to explore potential sources of bias. Such analyses could examine whether differences in data labeling practices or in the composition of annotator populations influence observed patterns in automatic emotion recognition. This could help reduce the risk of bias in emotion recognition technologies.

A Search Query Development

A.1 Scopus

Table 6 guides through the evaluative process of creating a search query that yields relevant and limited results.

Table 6: Iterative Development of the Scopus Search Query

Scopus Query	**Results**	**Evaluation**
ALL((emotion* OR feeling* OR mood* OR reaction* OR affect*) AND (perception OR perceive* OR understand* OR recogni*) AND ("individual differences" OR "individual characteristics" OR "individual traits" OR "perceiver traits" OR "perceiver differences" OR "perceiver characteristics" OR "perceiver context" OR subjectivity) AND (influence* OR bias* OR modulat* OR determin* OR effect OR affect*))	600,750	I joined the identified terms and their synonyms. The query is too wide. I will search for the terms only in the Titles/Abstracts/Keywords.
TITLE-ABS-KEY((emotion* OR feeling* OR mood* OR reaction* OR affect*) AND (perception OR perceive* OR understand* OR recogni*) AND ("individual differences" OR "individual characteristics" OR "individual traits" OR "perceiver traits" OR "perceiver differences" OR "perceiver characteristics" OR "perceiver context" OR subjectivity) AND (influence* OR bias* OR modulat* OR determin* OR effect OR affect*))	13,810	This is still too wide. I will remove some synonyms that are broad: *understand*, *mood*, and *reaction*.
TITLE-ABS-KEY((emotion* OR feeling* OR affect*) AND (perception OR perceive* OR recogni*) AND ("individual differences" OR "individual characteristics" OR "individual traits" OR "perceiver traits" OR "perceiver differences" OR "perceiver characteristics" OR "perceiver context" OR subjectivity) AND (influence* OR bias* OR modulat* OR determin* OR effect OR affect*))	7,833	The titles of the results do not seem to relate to my concepts. I will require the key concepts *emotion* and *perception* appear in the title.

TITLE((emotion* OR feeling* OR affect*) AND (perception OR perceive* OR recogni*)) AND TITLE-ABS-KEY(("individual differences" OR "individual characteristics" OR "individual traits" OR "perceiver traits" OR "perceiver differences" OR "perceiver characteristics" OR "perceiver context" OR subjectivity) AND (influence* OR bias* OR modulat* OR determin* OR effect OR affect*))	478	The synonym *affect** is often used with the meaning of influence rather than emotion, so I will remove it from the emotion concept.
TITLE((emotion* OR feeling*) AND (perception OR perceive* OR recogni*)) AND TITLE-ABS-KEY(("individual differences" OR "individual characteristics" OR "individual traits" OR "perceiver traits" OR "perceiver differences" OR "perceiver characteristics" OR "perceiver context" OR subjectivity) AND (influence* OR bias* OR modulat* OR determin* OR effect OR affect*))	353	Many results concern EEG-based emotion recognition models or mental disorders. I will exclude *EEG* and *disorder** from Titles/Abstracts/Keywords. I will not exclude *model** to avoid excluding relevant psychological models.
TITLE((emotion* OR feeling*) AND (perception OR perceive* OR recogni*)) AND TITLE-ABS-KEY(("individual differences" OR "individual characteristics" OR "individual traits" OR "perceiver traits" OR "perceiver differences" OR "perceiver characteristics" OR "perceiver context" OR subjectivity) AND (influence* OR bias* OR modulat* OR determin* OR effect OR affect*)) AND NOT(TITLE-ABS-KEY(EEG OR disorder*))	241	The term *model** relates to a lot of machine-learning-related papers. I will exclude *machine learning*, *deep learning*, and *automatic*.
TITLE((emotion* OR feeling*) AND (perception OR perceive* OR recogni*)) AND TITLE-ABS-KEY(("individual differences" OR "individual characteristics" OR "individual traits" OR "perceiver traits" OR "perceiver differences" OR "perceiver characteristics" OR "perceiver context" OR subjectivity) AND (influence* OR bias* OR modulat* OR determin* OR effect OR affect*)) AND NOT(TITLE-ABS-KEY(disorder* OR EEG OR "machine learning" OR "deep learning" OR "automatic"))	209	To narrow the results further, I will exclude papers focused on face masks, textual emotion recognition, developmental psychology, and music-related experiments by excluding *mask**, *child**, *text**, and *music**.

TITLE((emotion* OR feeling*) AND (perception OR perceive* OR recogni*)) AND TITLE-ABS-KEY(("individual differences" OR "individual characteristics" OR "individual traits" OR "perceiver traits" OR "perceiver differences" OR "perceiver characteristics" OR "perceiver context" OR subjectivity) AND (influence* OR bias* OR modulat* OR determin* OR effect OR affect*)) AND NOT(TITLE-ABS-KEY(EEG OR disorder* OR "machine learning" OR "deep learning" OR "automatic" OR child* OR mask* OR text* OR music*))	157	To ensure that emotion and perception are used together rather than separately, I will combine them with the `W/2` operator instead of `AND`.
TITLE((emotion* OR feeling*) W/2 (perception OR perceive* OR recogni*)) AND TITLE-ABS-KEY(("individual differences" OR "individual characteristics" OR "individual traits" OR "perceiver traits" OR "perceiver differences" OR "perceiver characteristics" OR "perceiver context" OR subjectivity) AND (influence* OR bias* OR modulat* OR determin* OR effect OR affect*)) AND NOT(TITLE-ABS-KEY(EEG OR disorder* OR "machine learning" OR "deep learning" OR "automatic" OR child* OR mask* OR text* OR music*))	**93**	This is a manageable number of papers given the available time. Five relevant papers previously identified through this process were searched for, and all five were included in the results. Further details are provided below*. **Chosen as Final Scopus Query**

*While trying different queries an initial screening of search results was conducted by reviewing titles for relevance to the inclusion criteria. Papers that clearly aligned with the research focus were kept in a validation set and used to test the sensitivity of the Scopus search strategy during iterative query refinement. The final query was validated using five representative studies:

- Kim et al. (2026) [42]
- Ensenberg-Diamant et al. (2025) [25]
- Shin et al. (2023) [69]
- Torok-Suri et al. (2025) [73]
- Furnes et al. (2019) [29]

A.2 PsychInfo

The final Scopus Query was adapted to match the PsycInfo search. This database does not recognize `W/2`-type proximity operators, so I used joint phrases for the concepts of emotion and perception (e.g., *emotion recognition*, *emotion perception*). I also mapped the Title/Abstract/Keyword strategy used in Scopus to the Ovid PsycInfo field structure by searching the most relevant concepts in the title field and the remaining concepts in the abstract field. Finally, I excluded the additional terms *schizophreni**, *autism*, and *depression*, as PsycInfo contains many studies focusing on clinical populations. These conditions are among the most commonly associated with differences in emotion perception. Although anxiety is also common in this literature, it was not excluded because the term may refer to a mood state rather than a clinical disorder.

The resulting final query for PsycInfo yielded **26** results and is the following:

(("emotion recognition" or "emotional recognition" or "emotion perception" or "emotional perception").ti. and ("individual differences" or "individual characteristics" or "individual traits" or "perceiver traits" or "perceiver differences" or "perceiver characteristics" or "perceiver context" or subjectivity).mp. and (influence* or bias* or modulat* or determin* or effect or affect*).ab.) not (EEG or disorder* or "machine learning" or "deep learning" or "automatic" or child* or mask* or text* or music* or schizophreni* or autism or depression).ab.

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