Artificial Intelligence in Emotion Recognition for Architectural Design: A Systematic Review

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***Abstract*—The growing convergence of neuroscience, artificial intelligence, and architectural design has given rise to innovative approaches for creating human-centered spaces that can sense and adapt to users' emotions. While numerous primary studies have explored AI-driven affective computing techniques using physiological and behavioral data to inform neuroarchitectural design, there is a notable lack of secondary studies that systematically synthesize these contributions particularly focusing on the specific AI algorithms employed and their role in emotion recognition processes. To address this gap, a systematic literature review was conducted to identify and analyze research published from 2015 to 2025 that examines AI algorithms, emotion recognition methods, and architectural stimuli influencing human emotional responses in physical spaces. The review aimed to answer the research question: "How are artificial intelligence algorithms being used to recognize emotions in architectural design contexts?". Searches were conducted across multiple digital libraries and conference proceedings, retrieving 167 papers, from which 24 were selected through predefined inclusion and exclusion criteria.. Fleiss' kappa statistics were applied to ensure inter-rater reliability during selection and data extraction. The results reveal a predominance of neural networks and deep learning approaches for multimodal emotion recognition, with color, geometry, and spatial organization as the most studied architectural stimuli. However, gaps remain in standardized assessment protocols, industry adoption, and real-world validations. These findings offer a consolidated view of the current state of AI-driven emotion recognition in architecture and provide guidance for researchers and practitioners to advance toward more robust, scalable, and emotionally intelligent built environments.**

***Keywords*—Artificial Intelligence, Emotion Recognition, Architectural Design, Neuroarchitecture, Machine Learning, Deep Learning, EEG, Affective Computing, Built Environment, Systematic Literature Review**

I. Introduction

In recent decades, architectural design has undergone a profound conceptual transformation, driven by emerging disciplines that place the human being at the center of spatial creation. One of the most prominent among these is neuroarchitecture, an interdisciplinary approach that investigates how the built environment influences human emotions, cognition, and behavior[3], [1].

By integrating insights from neuroscience into architectural design, neuroarchitecture aims to generate spaces that foster well-being, mental health, and overall quality of life[3], [36].

This field recognizes that spaces are not neutral environments: every architectural element from geometry and materials to natural lighting and spatial arrangement can modulate brain activity, influence the autonomic nervous system, and evoke specific emotional states[9], [39].

Studies have shown that architectural stimuli such as curved forms, soft lighting, or natural materials activate brain regions associated with memory and emotion, eliciting sensations of comfort, relaxation, or stimulation[4]. Thus, design transcends aesthetics and functionality to establish an emotional connection with users.

However, traditional approaches have largely relied on the designer's intuition or subjective aesthetic principles, lacking a solid empirical foundation to measure and optimize the emotional impact of architectural spaces[5].

In this context, neuroarchitecture draws on its historical and methodological foundations to establish a more rigorous conceptual framework. Is essential to contextualize this discipline within its precursors and to address terminological ambiguities in order to enrich the design process with tools that enhance users' cognitive and emotional well-being.

Simultaneously, virtual reality and electroencephalography (EEG) have emerged as key tools for empirically studying the interaction between humans and architectural environments[49]. Recent systematic reviews emphasize the importance of expanding research to include cognitive aspects such as creativity, critical thinking, and decision-making, as well as the need for longitudinal studies and culturally diverse population samples[49], [54]. Additionally, they recommend involving participants in active tasks during experiments and developing integrative methods to combine multidimensional data that reflect the cognitive, emotional, and physiological dimensions of architectural experience[54].

The use of neurophysiological data obtained through EEG aligns with a growing trend toward evidence-based, human-centered design. This approach enables designers to understand and respond to users' cognitive and emotional experiences within architectural spaces, thereby supporting more sensitive and effective design strategies[49], [27].

Despite these advances, the systematic integration of artificial intelligence AI into neuroarchitecture for the recognition and interpretation of human emotions in physical spaces remains in its early stages. While some studies address specific aspects such as the acquisition of unconscious parameters through EEG and electromyography (EMG), or bibliometric analyses of digital technologies in design there is a lack of comprehensive reviews examining how AI algorithms are transforming architectural design's ability to recognize, interpret, and respond to emotions induced by the built environment. Moreover, a clear categorization of emotional architectural stimuli and an in-depth analysis of hybrid methodologies that combine physiological data with advanced computational techniques are still needed.

A Systematic Literature Review (SLR) allows for the comprehensive and objective identification, evaluation, and interpretation of a research question, study area, or phenomenon of interest [38]. While several SLRs address neuroarchitecture in conjunction with emotion recognition and its effects, few focus specifically on how machine learning algorithms are being used to transform the architectural design's ability to recognize, interpret, and respond to emotions induced by the built environment.

Therefore, this article presents a systematic literature review on the use of artificial intelligence in emotion recognition for architectural design, with a focus on the machine learning algorithms employed to support this process. The main objective of this review is to understand how these algorithms are being applied and to identify which specific ones are most commonly used.

To achieve this, a rigorous methodology was followed. First, a search for primary studies was conducted in three digital libraries (ScienceDirect, ACM Library, and IEEE Xplore), yielding a total of 168 potential articles. Then, inclusion and exclusion criteria were applied in the first screening phase. Subsequently, domain experts reviewed the selected studies, and Fleiss' kappa statistic was used to measure inter-rater agreement. In the end, 24 relevant articles were selected.

In the next phase, data extraction criteria were defined and applied by all reviewers. Based on these criteria, a matrix was developed to systematize the information from all articles, allowing for the generation of statistics and knowledge to answer the research questions. The final step involved analyzing and discussing the results obtained.

Among the most relevant findings, the review revealed a marked preference for neural networks and deep learning techniques in emotion recognition systems applied to architectural design, highlighting their effectiveness in handling complex and multimodal data such as EEG signals and facial expressions. Nevertheless, classical algorithms such as SVM and KNN remain underused, suggesting opportunities for hybrid models. Additionally, the analysis identified key architectural features such as color, geometry, and spatial organization—as crucial for eliciting emotional responses, although the lack of standardized evaluation protocols limits comparability across studies. The review also highlighted that most studies are confined to academic settings, with minimal industry collaboration and limited real-world validation. Finally, it became evident that emotion modeling continues to rely on basic categorical frameworks, overlooking more nuanced dimensional approaches that could improve the responsiveness of design..

The remainder of this paper is structured as follows: Section II presents the background on neuroarchitecture and a brief overview of existing literature reviews in the field. Section III explains the research methodology. Section IV IV presents the results of the review. Section V discusses the findings and their limitations. Section VII provides the conclusions and suggests future research directions.

II. Background

This section addresses the relevance and application of algorithms in the fields of neuroarchitecture and affective computing. It also examines systematic reviews of the existing literature in this field.

A. ALGORITHMS IN NEUROARCHITECTURE, EMOTION RECOGNITION, AND AFFECTIVE COMPUTING

Algorithms are technological tools designed to process, analyze, and interpret complex datasets, deriving meaningful patterns that can inform and optimize interactions between humans and their environment [29]. In fields such as neuroarchitecture, emotion recognition, and affective computing, algorithms have gained prominence due to their ability to support human-centric design and enable adaptive, personalized experiences [24].

In neuroarchitecture, algorithms are crucial for assessing how architectural elements affect cognitive and emotional responses. For instance, machine learning approaches have been utilized to evaluate the impact of natural light, spatial distribution, and materials on neural activity, using signals derived from EEG, fMRI, or biometric data [24]. These algorithms translate neurophysiological data into actionable information, supporting the evidence-based design of environments that promote well-being and mental health [21].

Similarly, algorithms play an essential role in emotion recognition. Pattern recognition methods, such as convolutional neural networks (CNNs) and support vector machines (SVMs), are commonly employed to identify emotional states from facial expressions, vocal cues, or physiological signals [26]. These computational techniques allow for real-time detection of emotions, providing feedback not only in research environments but also in adaptive architectural systems that modify lighting, acoustics, or visual cues according to users' affective states .

Within affective computing, algorithms form the basis for enabling systems to detect, interpret, and appropriately respond to human emotions . These systems often integrate multimodal data—including facial movements, speech tone, and body gestures—processed through advanced machine learning and deep learning algorithms, such as recurrent neural networks (RNNs) and generative adversarial networks (GANs) . The resulting models can drive changes in the built environment, creating adaptive, emotionally intelligent spaces [24].

The effectiveness of these algorithmic approaches is contingent on several key factors: (i) the quality and multimodality of input data (e.g., EEG signals, video, audio), (ii) the complexity of the algorithm (e.g., supervised vs. unsupervised models), and (iii) the integration with feedback mechanisms that allow dynamic adjustment of architectural or digital environments [24]. For example, personalized lighting schemes in therapeutic settings may be controlled via algorithms that continuously analyze physiological stress markers, adapting the environment in real time to improve outcomes .

In summary, algorithms in neuroarchitecture, emotion recognition, and affective computing are bridging the gap between human experience and adaptive environments by providing objective, data-driven insights and responsive interventions. This technological evolution is paving the way for next-generation spaces optimized for cognitive and emotional well-being [22].

B. Existing systematic reviews

Several searches were conducted to identify systematic reviews relevant to the current study's domain. Searches were performed in digital libraries such as IEEE, ACM, and SpringerLink, as well as indexers like Google Scholar. The search string utilized was: (”NEUROARCHITECTURE” OR ”NEURO-ARCHITECTURE” OR ”NEURO”) AND (”SLR” OR ”SYSTEMATIC REVIEW” OR ”MAPPING” OR ”SURVEY” OR ”LITERATURE REVIEW”) AND (”AFFECTIVE COMPUTING” OR ”COGNITIVE”). This strategy allowed for the identification of three systematic reviews that specifically addressed the domain of neuroarchitecture.

First, Teherysayah et al. [49] conducted a systematic literature review to assess the impact of the environment on various aspects of individual experience, using virtual reality (VR) experiments combined with electroencephalography (EEG). The review also addressed the methods used to analyze EEG data, the measurement indicators employed, and their application in architectural design. In total, 19 studies that met the inclusion and exclusion criteria defined by the authors were analyzed. The findings showed a wide range of environmental effects on human states, demonstrating that factors such as color, shape, scale, and other elements of the environment can significantly influence aspects such as stress, attention, memory, orientation, and cognitive processing. It was also highlighted that brain activity and cognitive performance can be modulated by the built environment, and that there is remarkable consistency between cognitive responses observed in physical and virtual environments.

Second, Juan Luis Higuera Trujillo et al.[25] focuses on the various areas of study that have emerged around neuroarchitecture, emphasizing that architectural design impacts cognitive-emotional changes. In particular, it addresses the relationship between cognitive change and a geometric approach to space as perceived by the user. This perception can be highlighted through different methods of stimulus measurement, such as EEG, MEG, SNA, fMRI, and HRV, which serve as sources of metrics for implementing both physical and virtual environments. The authors conducted an extensive literature search, yielding 602 studies that met the defined acceptance criteria

Third, Llorens-Gámez et al.[34] conducted a systematic review focused on the impact of the design of learning spaces on cognitive processes, particularly attention and memory, from a neuroarchitectural perspective. The authors followed a rigorous methodology based on the Cochrane Handbook and PRISMA guidelines, identifying 14 studies published between 2007 and 2021 that met strict inclusion criteria regarding experimental design and cognitive assessment methods. The review categorized the analyzed design variables into six key domains: form and geometry, space distribution and context, color and texture, height and enclosure, transition and circulation, and environmental conditions such as light, sound, and temperature. The findings demonstrate that architectural design features such as ceiling height, color contrast, and spatial configuration can significantly affect both attention and memory in learning environments. Notably, several studies used EEG and fMRI to provide objective neurophysiological evidence of these effects. Despite methodological advances, the authors identified a lack of standardized protocols and cross-validated methodologies, highlighting the need for future research to deepen understanding of how specific environmental stimuli influence cognitive performance in educational spaces. This work underscores the importance of integrating neuroscientific tools into architectural research and reinforces the relevance of the built environment in modulating cognitive responses.

While existing systematic reviews have explored various facets of neuroarchitecture and affective computing, a gap remains regarding the explicit application of Artificial Intelligence (AI) algorithms in emotion recognition within physical spaces. For instance, some studies delve into neurocognitive impacts of architectural geometry and the use of physiological sensors like EEG and eye-tracking[45], [7], or explore interactive spatial experiences that adapt to emotional states through wearable technology and AI [20]. Others investigate smart environmental design for artificial empathy via facial and postural recognition[40], or focus on AI-driven spatial adaptations based on facial emotion recognition[43]. However, the current body of work lacks a comprehensive and structured analysis of how specific AI algorithms are being implemented in affective computing specifically for neuroarchitecture. This review aims to bridge that gap by addressing how AI algorithms are being used to interpret human emotions in relation to the physical environment, and the methodologies employed in this research area. We will particularly focus on identifying the types of architectural stimuli analyzed in affective computing studies and the specific AI algorithms utilized to assess their impact on human emotional responses within designed spaces. Therefore, this systematic review seeks to provide a clearer understanding of the current landscape of AI integration in neuroarchitecture's affective computing domain, offering valuable insights for future research and practical applications.

III. Research Method

This systematic literature review was conducted following the methodology proposed by Kitchenham[32]. Each stage was rigorously followed to ensure transparency, reproducibility, and methodological soundness in the selection, evaluation, and synthesis of studies.

A. Planning the review

This section outlines the general planning of the systematic review, detailing the methodological approach adopted, the research questions, the criteria for searching and selecting studies, as well as the strategy for data extraction and analysis. The entire process has been structured to ensure rigor and consistency in the identification and synthesis of the available evidence.

1) PICOC Methodology: To frame the scope of the review, the PICOC (Population, Intervention, Comparison, Outcomes, Context) framework was applied. This approach helped structure the research problem and align the research questions with the selection of relevant studies. The specific components of the PICOC framework used in this review are detailed in Table I.

TABLE I
PICOC Outcomes

Stages	Description
Population	Architects, clients, and researchers or developers working with affective computing
Investigation	The use of affective computing techniques in architectural design development
Comparison	Traditional architectural design approaches that do not integrate affective computing or AI technologies
Outcomes	Analyze the implementation of artificial intelligence algorithms related to affective computing in architectural design, exploring how these technologies influence human emotions and spatial experiences, while identifying their limitations within the context of neuroarchitecture
Context	Interdisciplinary studies published from 2015 onwards, focusing on the intersection of architecture, neuroscience, and artificial intelligence. This year marks a milestone in the practical development of emotion recognition systems based on facial expression analysis, speech, gestures, and physiological signals advancements aimed at enhancing human-computer interaction in contexts such as mental health, education, and entertainment [47]

2) Research Questions: This SLR focuses on affective computing as a tool for evaluating the design of physical spaces, within the framework of neuroarchitecture. During the literature review, it was observed that existing systematic reviews [49], [25] only superficially mention or do not specify the artificial intelligence algorithms used for emotion recognition, highlighting a significant gap in the current literature. Therefore, the main research question is: How are artificial intelligence algorithms used in the recognition of emotions in physical spaces? To address this question, the following subquestions have been formulated: a) What types of architectural stimuli are analyzed in affective computing studies to evaluate their impact on human emotional responses?, b) Which artificial intelligence algorithms are used to interpret human emotions in relation to the physical environment?, c) How is research being conducted regarding the design of physical spaces and its relationship with affective computing?.

3) Research Strategy: A search strategy was defined to ensure a comprehensive and unbiased identification of studies. The selected sources included four primary digital repositories: ACM Digital Library, IEEE Xplore Digital Library, ScienceDirect, and Google Scholar as a general academic indexer. In addition, manual searches and a snowballing strategy were employed using the Litmap web application to broaden the scope of the review and identify relevant works that might not appear through database queries alone.

One notable milestone within the scope of this review is the study titled "Analysis of EEG signals and facial expressions for continuous emotion detection"[47], published in IEEE Transactions on Affective Computing. This work demonstrated the potential of electroencephalography (EEG) signals in detecting emotional states, particularly in identifying positive emotional valence. While facial expressions yielded better performance in emotion detection, EEG signals still proved valuable, especially in scenarios where facial data is unavailable. This highlights the importance of EEG-based approaches in fields such as neuroarchitecture, where understanding emotional responses to physical spaces can inform the design of environments

A manual search was also conducted in conferences and journals to identify studies that were not retrieved through the automatic search previously described. Table IIpresents the results of this manual search.

TABLE II
Conferences and Journal Selected to Manual Search

Conferences	Core
International Conference on Human Factors in Computing Systems	A*
International Conference of Computational Methods in Engineering Science	A
Education and Research in Computer Aided Architectural Design in Europe (eCAADe)	B
Association for Computer Aided Design in Architecture (ACADIA)	A
Journal	
Applied Sciences	Q1
Architectural Science Review	Q1
Building and Environment	Q1
Ain Shams Engineering Journal	Q1
International Journal of Architectural Computing	Q2
Civil Engineering and Architecture	Q2

4) Selection criteria for primary studies: To guide the selection of studies within the systematic review process, inclusion criteria define the conditions under which a study is considered relevant and eligible for analysis. Conversely, exclusion criteria serve to filter out studies that, although initially retrieved, do not meet the necessary standards for inclusion. This approach ensures that only the most pertinent research is considered.

A thorough inspection of the titles, abstracts, and conclusions of the retrieved papers was conducted to determine their suitability. This semantic check was crucial, as initial search results may not always perfectly align with the review's specific research area. Based on this detailed examination, papers were accepted or rejected according to the guidelines outlined in Table III.

TABLE III
SELECTION CRITERIA

Inclusion Criteria
Apply affective computing techniques, including emotion analysis using artificial intelligence, biometric sensors, computer vision, voice processing, among others
Are related to physical or architectural environments, such as smart spaces, interior design, urban planning, institutional buildings, or neuro architectural proposals
Evaluate or measure the emotional or neurocognitive response of users within an architectural environment
Are published in peer-reviewed scientific journals, conference proceedings, or academic books
Exclusion Criteria
Address affective computing without involving physical space design or the arrangement of elements in a physical environment
Were published before 2015
Are introductory or theoretical overviews without original research
Are not scientific articles or conference papers
Are short publications with fewer than 5 pages
Are written in a language other than English
Are duplicated in different sources
Do not constitute primary research

5) Data Extraction Strategy: In order to answer the sub-questions, extraction criteria have been defined for each of them. These are shown in Table IV.

Single-modal Affect Recognition(EC1)
This term focuses on a set of methods that aim to identify effects or stimuli originating from a single sensory modality. For example, in the case of text, textual analysis is a method used to identify subtle sentiments or emotions, whether expressed explicitly or implicitly, from user-generated data[50]. The approaches within this methodology typically rely on feature engineering to uncover these subtle

TABLE IV
DATA EXTRACTION CRITERIA

RQ1: How are artificial intelligence algorithms being used in emotion recognition for physical spaces?

EC1.Single-modal Affect Recognition
- ☐ Text sentiment analysis
- ☐ Audio emotion recognition
- ☐ Physiological-based emotion recognition
- ☐ Visual emotion recognition

EC2.Base Approaches to the Cognitive-Emotional Dimension of Architecture
- ☐ Geometry
- ☐ Experience of space and its geography
- ☐ Philosophy of physical spaces
- ☐ Psychology of a physical environment
- ☐ Experience-based design

RQ2: What types of architectural stimuli are being analyzed in affective computing studies to assess their impact on human emotional responses?

EC3.Emotion recognition method based on measurement of electrical parameters
- ☐ Based on direct sensors
- ☐ Based on modular sensors

EC4.Emotion recognition method based on the measurement of non-electrical parameters
- ☐ Contact measurements
- ☐ Non-contact measurements

EC5.Perception and organization of elements
- ☐ Proximity
- ☐ Similarity
- ☐ Figure and ground
- ☐ Closure
- ☐ Continuity

EC6.Psychological aspects applied to art
- ☐ Symmetry
- ☐ Visual point
- ☐ Color
- ☐ Complexity
- ☐ Proportion
- ☐ Order

EC7.Models of emotion assessment
- ☐ Russel's Circumplex Model
- ☐ Dimensional Models
- ☐ Discrete Categories

RQ3: What artificial intelligence algorithms are being used to interpret human emotions in relation to the physical environment?

EC8.Function of the algorithm
- ☐ Classification
- ☐ Clustering
- ☐ Regression
- ☐ Real-time detection

EC9.AI Algorithms
- ☐ Neural Network
- ☐ Ensemble Methods
- ☐ Support Vector Machine(SVM)
- ☐ Deep Learning
- ☐ K-Nearest Neighbors(KNN)
- ☐ Others
- ☐ No specific

RQ4: How is research being conducted in this area?

EC10.Validation
- ☐ Proof of concepts
- ☐ Survey
- ☐ Experiment
- ☐ Study case
- ☐ Quasi experiment
- ☐ No specification
- ☐ Others

EC11.Approach scope
- ☐ Industry
- ☐ Academy

EC12.Methodology
- ☐ New
- ☐ Extension

characteristics related to a subject's feelings. This same approach allows for the identification of other stimuli, such as visual and auditory cues, and emotion recognition based on physiology.

Base Approaches to the Cognitive-Emotional Dimension of Architecture(EC2)

Cognitive-emotional research has shown particular interest in architectural space. The basis of its approaches lies in three fundamental pillars: geometry, phenomenology of space and geographical experience, and philosophy, environmental psychology, and evidence-based design. The geometric approach focuses on the proportions and visual harmonies of design in an effort to generate feelings of balance. The phenomenology of space and geographical experience explores how individuals subjectively and sensually experience their surroundings. Finally, philosophy, environmental psychology, and evidence-based design encompass the mental processes behind one's interaction with the environment[25].

Emotion recognition method based on measurement of electrical parameters(EC3)

These methods focus on detecting and analyzing electrical signals generated by the human body. Specifically, they center on changes in the body's electrical properties that are modulated towards a sensor. There are two main types of sensors utilized: direct sensors and modulating sensors. Direct sensors include EEG (Electroencephalography), ECG (Electrocardiography), HRV (Heart Rate Variability), EMG (Electromyography), and EOG (Electrooculography). An example of a modulating sensor is GSR (Galvanic Skin Response)[11].

Emotion recognition method based on the measurement of non-electrical parameters(EC4)

These methods do not rely on direct electrical signals but rather on other physical or physiological characteristics of the body. Their primary advantage lies in the ability to perform non-contact measurements, which minimizes limitations on human activity and makes them ideal for field applications and approximate emotional state evaluations. However, they are typically subject to lower precision and greater latency when compared to the previously defined electrical methods[11].

Perception and organization of elements(EC5)

Refers to how people interpret and group visual elements in an architectural or virtual environment. This criterion is based on principles of Gestalt psychology[25], such as proximity, similarity, closure, continuity and figure-ground, which explain how visual stimuli are organized to form coherent perceptions. These principles directly influence how users perceive space and respond emotionally to it.

Perception and organization of elements(EC6)

It focuses on the psychological principles that influence the aesthetic and emotional perception of designed spaces. It includes elements such as symmetry, which facilitates the perception of order by organizing elements around a central point, and color, processed in early stages of vision, with diverse effects on aesthetic preferences and emotional state [25]. Complexity is also considered, where a preference for moderate levels evoking natural environments such as the savannah is observed. The prospect-refuge principle suggests that people prefer environments that combine visibility of the surroundings and safe places to take refuge. In addition, proportion, such as the golden section, is associated with greater aesthetic appeal, and order, when balanced with complexity, enhances visual comprehension and aesthetic appreciation of space. Together, these factors guide how art and architectural design affect the psychological experience of the user.

Models of emotion assessment(EC7)

Dimensional models typically conceptualize emotions as points represented within a two-dimensional or three-dimensional region. The two-dimensional representation is primarily defined by valence and arousal. Valence determines the positive or negative level of an emotion, while arousal dictates the degree of excitation or intensity of the emotion. The addition of an extra dimension leads to a three-dimensional representation, which includes dominance. Dominance expresses the degree of human control over an emotion. A prominent implementation of this concept is Russell's Circumplex Model, which proposes that emotions are distributed circularly around a central point in a two-dimensional space of valence and arousal[16].

Function of the algorithm(EC8)

Refers to the operational purpose served by the algorithm within the data processing system. Among the most common functions are classification, which assigns instances to predefined categories; clustering, which organizes data into groups based on similarity without the need for prior labels; regression, which predicts continuous values from input variables; and real-time detection, which allows immediate identification of patterns as data are received. These functions can be implemented using approaches such as density estimation, boundary delimitation, or reconstruction methods, especially in one-class learning models that operate on positive or partially labeled data [13]. The choice of algorithm function determines how the data is structured, interpreted and processed within the system.

Function of the algorithm(EC9)

A multitude of artificial intelligence algorithms are employed for emotion recognition. Among the prominent ones are neural networks, whose operations are inspired by human neural networks. They are considered a supervised learning technology and are utilized for both regression and classification algorithms. Similarly, Support Vector Machines (SVMs) are regarded as methods for both classification and regression. Another fundamental algorithm is K-nearest neighbor (KNN), which is based on the supervised learning technique. The KNN algorithm categorizes new data points based on their similarity to existing ones, allowing for rapid processing of new information[52].

Approach scope(EC10)
Six types of criteria were applied. When a particular kind of research aims to answer a question whose answer has broad applicability in areas beyond that tested, it is a Proof of concept [30]. A survey is designed to quantify and universalize the information and standardize the interview procedure [48]. Then, a quasi-experiment is an experiment where subjects are not randomly assigned to groups [23]. Similarly, but not the same, an experiment refers to any non-randomized study that compares treatment to a control group without specific requirements on how the treatment is assigned [23]. Therefore, a prototype is an object that is a reference for future production models. It is one of the first devices to be manufactured, from which errors are evaluated and corrected, and the most relevant ideas are taken to construct other designs [37]. Finally, a case study studies a contemporary phenomenon within its natural context, in which the boundaries between the phenomenon and the context are not visible, and different sources of evidence are used [6].

Approach scope(EC11)
This criterion is related to the approach of the work, whether it was developed in industry or academia.

Methodology(EC12)
This criterion refers to whether the research is new or is an extension of previous research.

B. Conducting the Review

The planning, execution, and identification of primary studies were carried out in May 2025. A total of 167 research papers were retrieved from digital libraries through an automated search strategy: 109 from IEEE Xplore, 58 from the ACM Digital Library, and 29 from ScienceDirect. Manual search was also conducted to complement the automated results, yielding 18 papers. Following this, the primary studies underwent a rigorous selection process based on predefined inclusion and exclusion criteria. Each article was carefully reviewed to determine its eligibility. After this detailed analysis, 24 primary studies were finally selected to form the basis of this secondary study.

IV. RESULTS OF THE SYSTEMATIC REVIEW

The results of the review are discussed in the following subsections. Subsection IV-A presents a discussion criterion by criterion, subsection IV-B shows trends and gaps between the criteria, and subsection IV-C discusses the results by country and year. In this way, each RSQ of the review was answered.

TABLE V
REVIEW RESULTS BY SOURCE

Source	Automatic Search	Final Review
Digital Libraries		
IEEEXplore	109	0
ACM	58	4
ScienceDirect	29	3
Conferences		
International Conference on Human Factors in Computing Systems		1
International Conference of Computational Methods in Engineering Science		1
Education and Research in Computer Aided Architectural Design in Europe (eCAADe)		3
Association for Computer Aided Design in Architecture (ACADIA)		2
Journals		
Applied Sciences		2
Architectural Science Review		3
Building and Environment		1
Ain Shams Engineering Journal		2
International Journal of Architectural Computing		1
Civil Engineering and Architecture		1
Total	167	24

A. Criterion by criterion results

In this subsection, each extraction criterion and its obtained results are analyzed. The table VI denotes the number of articles in which each criterion is present and its respective percentage.

1) Single-modal Affect Recognition(EC1): The analysis of the reviewed studies indicates that single-modal approaches to affect recognition are primarily dominated by visual emotion recognition and physiological-based emotion recognition, together comprising 54% of the methods identified. Visual emotion recognition most commonly relies on decoding facial expressions and body gestures, with notable implementations such as computational layers integrated into physical spaces, where detected emotions are translated into light projections reflected by mirrors whose curvature dynamically adjusts to mirror emotional states [40]. Physiological-based emotion recognition frequently involves metrics such as fMRI, EEG, BVP, and GSR, with experiments leveraging these signals to optimize architectural spatial elements in real-time within virtual reality environments, where algorithms dynamically adapt virtual scene elements based on users' physiological responses [53].

The literature also identifies a significant emphasis on visual cues in broader emotion recognition systems. Visual features, particularly facial expressions, remain a cornerstone for detecting subtle affective states and fostering empathetic interactions among users [40][41][15]. Complementarily, audio emotion recognition plays a secondary yet noteworthy role, often in the context of video-based systems. These studies typically employ traditional and deep learning classifiers trained on handcrafted audio descriptors such as Mel Frequency Cepstrum

TABLE VI
DATA EXTRACTION CRITERIA RESULTS

Extract criteria	Count	%
EC1.Single-modal Affect Recognition		
Text sentiment analysis	2	8
Audio emotion recognition	5	20
Visual emotion recognition	13	54
Physiological-based emotion recognition	13	54
EC2.Base Approaches to the Cognitive-Emotional Dimension of Architecture		
Geometry	13	54
Experience of space and its geography	10	41
Philosophy of physical spaces	10	41
Psychology of a physical environment	15	62
Experience-based design	15	62
EC3.Emotion recognition method based on measurement of electrical parameters		
Based on direct sensors	17	70
Based on modular sensors	7	29
EC4.Emotion recognition method based on the measurement of non electrical parameters		
Contact measurements	7	29
Non-contact measurements	12	50
EC5.Perception and organization of elements		
Proximity	6	25
Similarity	5	20
Figure and ground	10	41
Closure	1	4
Continuity	1	4
EC6.Psychological aspects applied to art		
Symmetry	7	29
Visual point	4	16
Color	16	66
Complexity	7	29
Proportion	9	37
Order	8	33
EC7.Models of emotion assessment		
Russel's Circumplex Model	0	0
Dimensional Models	4	16
Discrete Categories	12	50
EC8.Function of the algorithm		
Classification	10	41
Clustering	4	16
Regression	1	4
Real-time detection	3	12
EC9.AI Algorithms		
Neural Network	7	29
Ensemble Methods	1	4
Support Vector Machine(SVM)	2	8
Deep Learning	2	8
K-Nearest Neighbors(KNN)	7	29
Others	4	16
No specific	6	25
EC10.Validation		
Proof of concepts	5	20
Survey	1	4
Experiment	14	58
Study case	4	16
Quasi experiment	2	8
No specification	1	4
Others	0	0
EC11.Approach scope		
Industry	1	4
Academy	24	100
EC11.Methodology		
New	23	95
Extension	1	4

Coefficients (MFCC) or spectrograms [51], underscoring audio's relevance despite its lower prevalence compared to visual and physiological modalities.

Conversely, there is limited representation of text sentiment analysis and direct applications of physiological signals such as EEG or ECG in isolated single-modal frameworks. However, recent studies demonstrate the feasibility of unimodal EEG-based emotion recognition in architectural contexts, such as fine-tuned AI models achieving 60.3% accuracy in classifying emotions (positive, neutral, negative) within adaptive VR environments[42].

2) Base Approaches to the Cognitive Emotional Dimension of Architecture(EC2): The reviewed studies highlight that the cognitive-emotional dimension of architecture is primarily grounded in the interaction between geometry and the psychology of physical environments (62%). Central to this is the notion of living geometry, described as a universal set of mathematical and geometrical properties—such as fractal scaling, nested symmetries, and coherence—mirroring biological and natural forms inherently aligned with human cognition and well-being [44]. These geometrical patterns are deeply connected to neurophysiological and evolutionary mechanisms, as the human brain is predisposed to favor ordered complexity, while deviations from these principles may induce stress and cognitive dissonance [44][35]. Thus, geometry is not treated as an aesthetic variable alone but as a determinant of psychological and physiological outcomes [10][44][35].

In parallel, the psychology of the physical environment emerges as a complementary foundation. Findings highlight the concept of alloplasticity, where the environment can be psychologically manipulated to help individuals adapt to specific circumstances. Technologies like intelligent mirrors exemplify this, generating artificial auto-empathy through reflected emotional states, functioning as an autoplastic process in which spaces respond to and mirror the user's emotions [40]. Together, geometry and environmental psychology form a scientific basis for designing spaces that actively support emotional regulation and cognitive performance.

These principles directly extend to the experience of space and its geography, and experience-based design. Studies reveal that spatial factors—including scale, proportion, protrusion, and curvature—directly influence users' emotional reactivity, with evidence showing that larger-scale virtual spaces can elicit more positive emotional responses compared to smaller ones [45]. Emerging fields like neuro-adaptive architecture employ sensors and AI to monitor occupants' psychological states, dynamically modulating lighting, acoustics, or spatial configurations to foster well-being [35][44]. Notably, frameworks such as the Human-Building Foundation Model (HBFM) integrate multimodal neural, behavioral, and linguistic data to bridge architectural intentions with quantifiable human experiences[33].

The philosophy of physical spaces is implicitly redefined. Sources advocate for a paradigm shift from traditional aesthetics and functionalism towards a human-centered model grounded in neuroscience and biology, prioritizing occupant flourishing [46]. Within this framework, experience-based design operates as the practical implementation of living geometry and environmental psychology, enabling emotionally intelligent, scientifically informed environments that enhance human health and cognition [45][51][10][46]. Collectively, these approaches present a cohesive strategy for integrating cognitive-emotional considerations into architectural practice.

3) Emotion recognition method based on measurement of electrical parameters(EC3): The direct sensory dimension (70%) has enabled the objective measurement of emotional reactivity to architectural space through physiological and neurological data. In study [45], sensors such as EEG, GSR, eye tracking, and fMRI were employed to analyze how geometric factors including scale, curvature, and symmetry influence cerebral aesthetic activation and indicators like pupil dilation, visual fixations, and subjective interest. Large and curved spaces generated more positive emotional responses, particularly in non-designer users. In parallel, real-time EEG-driven systems in VR architectural environments have shown promise in dynamically adjusting lighting and spatial configurations based on detected emotions (e.g., enhancing natural light for positive states), though with moderate accuracy[33]. Complementarily, the use of eye tracking in [7] allowed for the classification of spaces as relaxing or stressful based on pupillary data, utilizing machine learning algorithms such as decision trees and logistic regression. In [20], wearable technologies like Empatica E4 and OpenBCI EEG were integrated into interactive installations to spatially transform environments according to detected emotional responses. Finally, details an adaptive cyber physical architecture that, using biological (GSR, BVP, TEMP) and neurological data, predicts and responds in real-time to seven discrete human emotions with 89% accuracy, generating a dynamic interaction between the user and the space[19].

4) Emotion recognition method based on the measurement of non- electrical parameters (EC4): Several studies have demonstrated the potential of physiological and neurological measurements within the realm of adaptive architectural design. For example, [19] developed an interactive cyber-physical architectural space that utilized non-invasive sensors, such as the Empatica E4 and portable EEGs, to collect physiological data (heart rate, temperature, skin conductance, blood pressure) and neurological data (brain waves). This information was then used to predict seven discrete human emotions. The data was processed with machine learning algorithms and neural networks, achieving an 89% accuracy in emotional detection. The "Wisteria" interactive installation integrated these capabilities, dynamically adapting the space's volume and lighting based on the occupants' emotional states, thereby facilitating an immersive and emotionally resonant experience. In a complementary approach, [53] employed EEG signals and eye-tracking techniques to optimize architectural elements in real-time, without requiring conscious user intervention. Through an iterative process in virtual reality scenarios, the system adjusted spatial parameters such as color, size, and distribution, thereby enhancing user psychological well-being. Similarly, [40] introduced a multilayer model called "The City of Emotions," which uses robotic mirrors and analyzes facial expressions and postures via tools like AffdexSDK and PoseNet. These technologies enable the decoding of emotions and the real-time transformation of the physical environment through light, color, and movement, fostering self-empathy and an indirect emotional interaction between the space and the individual.

5) Perception and organization of elements (EC5): The reviewed studies demonstrate that geometric and compositional elements of space significantly impact emotional perception. For instance, [45] showed that proximity and spatial similarity influence emotional activation, as measured by physiological indicators such as EEG, GSR, and eye tracking. This research found that spacious and symmetrical environments generated higher levels of positive subjective interest and satisfaction, while narrow or aggressively geometric configurations evoked emotional discomfort, especially in users without design training. Furthermore, the figure-ground principle was addressed in several studies. In [20] and [40], interactive installations and reflective surfaces were employed as perceptive mechanisms to induce emotional self-empathy, utilizing visual elements that either highlight or conceal themselves based on the user's position and the flow of the space. These strategies allow architectural environments to function as "emotional mirrors," modifying the surroundings in real-time through light, form, and movement. Additionally, [45] highlighted how curvature and visual fluidity are preferred over angular forms, aligning with the law of continuity in perceptual organization. These characteristics activate brain areas associated with aesthetic processing, even in users without professional training, suggesting a universality in emotional responses to certain geometric patterns. However, factors beyond geometry such as lighting, materiality, and 360° visualization—have been identified as critical for perceptual realism and emotional impact in virtual architectural spaces, suggesting that geometry is not the only element that shapes user experience[42].

6) Psychological aspects applied to art (EC6): Empirical findings indicate that color is the element most consistently linked to user emotional responses, appearing in 66% of the analyzed studies. In research such as [53], [31], [19], [14], [20], and [40], color was employed as a key variable to evoke emotional responses in both physical and virtual environments. These studies concur that certain warm and natural colors generate greater emotional comfort, while cool or artificial hues can induce feelings of discomfort or emotional coldness[42]. Symmetry emerges as another relevant factor, present in 29% of the studies, including [53], [31], [43], and [45]. Specifically, [45] found that symmetrical compositions and regular geometric proportions activate brain regions associated with aesthetic processing, even in subjects without design training. Regarding complexity, studies [53] and [43] indicate that intermediate levels, which evoke natural patterns like those observed in open landscapes with refuges, tend to be perceived as emotionally positive. These environments stimulate richer and more pleasurable visual exploration without leading to cognitive overload. Proportion and visual order also play a significant role. In studies [53], [19], and [20], harmonious visual proportions, such as the golden ratio, were applied to guide attention and generate aesthetic pleasure.

7) Models of emotion assessment(EC7): The studies reviewed show a strong preference for the use of discrete categories of emotions over dimensional representations. In 50% of the studies ([19], [14], [43], [20], [28]), emotions were classified into specific categories such as happiness, sadness, fear, surprise, anxiety or security, associated with architectural stimuli and measured by sensors such as EEG, GSR or facial recognition. These categories also included simple affective responses such as "liking," "neutral," or "disliking" [8]. For example, feelings of calmness were reported in 2D environments, whereas more intense emotions such as fear, anxiety or stress were observed in virtual environments ([42][15][18][8]). These approaches prioritize the practical observation and differentiation of specific emotional states, using physiological data such as EEG, considered a suitable method for affective analysis [8].

In contrast, only 16% of the studies used dimensional models, such as the measurement of valence and activation by means of psychophysiological techniques, exemplified in [31]. No direct mentions or explicit applications of Russell's Circumplex Model or other general dimensional models were found, reflecting that the analyzed research prioritizes categorical assessment over continuous representation of emotional states. Taken together, these results evidence a trend toward discrete emotion classification as the predominant method for linking affective responses to architectural features and virtual contexts.

8) Function of the algorithm(EC8): The most frequently utilized artificial intelligence method in the analyzed studies was classification, appearing in 41% of the works ([31], [7], [33], [15], [28],[18],[8]). In these studies, algorithms classified physiological or behavioral responses into specific emotional categories, enabling the dynamic adaptation of architectural environments based on the user's state. Clustering was identified in 16% of the studies ([53], [31], [7]). This method was employed to group patterns of behavior or brain activity without prior labeling, allowing for the discovery of emergent emotional profiles from the data. This approach proves useful when an exploratory segmentation of users based on their spatial perception is desired. Regression, at 4%, was present in study [19], where it was used to predict continuous emotional values derived from physiological signals. While this approach offers a more nuanced representation of emotional response, its low frequency of use suggests it has not yet been widely adopted in affective architectural design. Furthermore, real-time detection was applied in 12% of the studies ([31], [40]). This method is crucial for implementing intelligent environments capable of instantaneously adapting to a user's emotional state. Such systems demand highly efficient, low-latency algorithms, as they continuously process data streams from sources like EEG, GSR, or computer vision.

9) Function of the algorithm (EC9): The papers demonstrate that neural networks were employed in 29% of the studies ([53], [19], [43], [7]), highlighting their use as a central tool in affective computing systems applied to architectural spaces. This approach was further bolstered in some cases by deep learning, also present in 29% of the articles ([43], [40], [19],[33],[28],[18],[8]), particularly in projects requiring complex analysis of physiological signals or facial images. The KNN algorithm was utilized in 8% of the studies ([53], [7]), primarily due to its simplicity and speed in categorizing emotions through similarity. In contrast, SVM, despite its recognized efficacy, had minimal presence, identified in only 4% of the works ([7]). Other approaches were reported in 16% of the cases ([53], [19]), encompassing diverse techniques not classified among the traditional models. Conversely, 25% of the studies did not specify the algorithm used ([31], [20], [14], [45]), suggesting a lack of methodological transparency or an early stage in algorithmic implementation.

10) Validation (EC10): The validation strategies among the analyzed studies present a diverse but focused trend. Implementation appears as the most recurrent validation phase, with 22 papers (45%) incorporating this stage, followed by Design (20 papers, 41%), and Testing (16 papers, 33%). Meanwhile, Analysis was addressed in 14 studies (29%). Some papers combine these phases, reflecting a holistic methodological approach (e.g., [42], [33], [15], [2], [28], [18]). Particularly, a subset of papers conducts thorough testing using EEG-based methods and emotion recognition systems, offering experimental and measurable validation (e.g., [28], [8], [45]). Others rely on immersive simulations or interactive systems in architectural contexts to observe emotional feedback (e.g., [2], [18], [19]). However, a limited portion explicitly engages in industry-based validation or real world deployment scenarios. Only one study ([15]) is noted to involve both academic and industry collaboration during validation, showing limited industry involvement. Overall, validation is strongly oriented toward academic prototypes and lab-tested environments, indicating a need for broader, applied validations in future studies.

11) Approach scope (EC11): An overwhelming majority of studies (100%) are affiliated with academia, confirming that this field is predominantly explored in research institutions. Only one paper ([15]) is explicitly identified as involving industry, resulting in a mere 4% representation.Some papers indirectly suggest connections with applied contexts or real life architectural practice, such as those using EEG or affective computing tools in designed environments (e.g., [8], [28]), but these remain primarily academic led. There is no significant trend indicating consistent academia–industry collaboration, suggesting a gap in translational research and the practical application of affective computing in architectural design. This academic dominance reflects an exploratory stage of the field, where conceptual and experimental developments are prioritized over direct industry integration.

12) Methodology (EC12): Most papers (95%) propose novel contributions, either through frameworks, models, or systems aiming to integrate affective computing into architecture and design. Only a minority (4%, one study: [17]) is classified as an extension or evolution of an existing solution. These new contributions range from neural network architectures for emotion detection (e.g., [12], [41], [28]), to AI-driven emotional spatial adaptations (e.g., [43]), and empathy-based design tools (e.g., [19], [20], [40]). Affective computing techniques are frequently developed from the ground up, indicating a high degree of innovation and conceptual groundwork. This strong inclination toward originality emphasizes the field's novelty and the ongoing formulation of foundational tools and theories.

B. Relations between criteria

This subsection identifies thematic gaps, disconnections, and asymmetries among the defined extraction criteria (EC1–EC12), offering a critical perspective on underexplored dimensions within affective architectural research. A noticeable disparity exists between EC3 (electrical physiological parameters) and EC4 (non-electrical physiological parameters). While both criteria focus on physiological measurement, EC3 demonstrates a greater variety of validated technologies, such as EEG, GSR, and eye tracking. Conversely, EC4 exhibits less methodological diversity. Similarly, EC2 (spatial cognition and emotional perception's theoretical underpinnings) and EC5 (geometric and perceptual principles), though both addressing spatial cognition and emotional perception, differ in their primary focus. EC2 concentrates on theoretical foundations and cognitive-affective models, while EC5 leans towards geometric and perceptual principles. Integrating both approaches would allow for the construction of a more holistic emotional-spatial interaction framework. Another gap is detected between EC6 (color, proportion, and symmetry) and EC7 (emotional modeling). While EC6 provides robust findings regarding color, proportion, and symmetry, emotional modeling within EC7 appears fragmented. This is characterized by a marked imbalance between discrete and dimensional approaches, along with limited cross-validation with perceptual data. Similarly, EC8 (algorithmic function) and EC9 (algorithmic function's specific types) reveal a methodological bias. There is an evident inclination towards classification techniques and the use of neural networks, respectively, while approaches such as clustering, regression, and hybrid artificial intelligence models are underutilized.

C. Results by year and by country

Figure 3 illustrates the distribution of publications by year, distinguishing between articles identified through automated and manual searches, as well as the consulted sources (journals and conferences). The systematic review encompassed publications from 2015 to the present, a period that clearly demonstrates an upward trend in scientific output related to affective computing applied to architecture and design. The year 2025 stands out as the most prolific, with a total of five relevant publications, indicating a growing interest and consolidation of the field. This surge coincides with the advancement of emerging technologies such as virtual reality, the metaverse, and cyber-physical systems applied to emotion-sensitive architectural environments. The years 2024 and 2023 follow closely with three publications each, solidifying a recent period of high production that reflects a dynamic academic and research environment. From 2020 onward, there has been a stabilization, with a consistent average of two to three publications per year, while earlier years show a more dispersed and sporadic output. Regarding geographic distribution (see Figure 2), the United States demonstrates leadership with six publications, positioning the country as a primary reference in the intersection of artificial intelligence, emotions, and architectural design. South Korea and India follow, each with two publications, reflecting the growing interest of Asian countries in developing neuro-adaptive solutions and intelligent systems applied to spatial perception. Other notable contributors include China, Germany, Italy, Poland, and Egypt, with specific contributions that highlight a global and diverse approach to exploring emotionally sensitive design. Latin America is represented by Peru, which, although incipient, signals an opening towards these technologies within regional architectural contexts.

V. DISCUSSION

The results of the presented SLR were used to answer the SRQs formulated at the initial stage. First, regarding the use of AI algorithms in emotion recognition (EC1, EC8, EC9), the studies revealed a predominant use of neural networks (29%) and deep learning (29%) in architectural contexts. These approaches are particularly efficient for processing complex data types like EEG and facial expressions. However, other algorithms such as Support Vector Machines (SVMs, 4.17%) and K-Nearest Neighbors (KNN, 8.33%) remain underexplored despite their potential for high-performance classification. This highlights a tendency to favor deep learning approaches, likely due to their accuracy in multimodal data fusion. Future work could benefit from investigating hybrid AI models that integrate both neural and classical algorithms to enhance both interpretability and robustness.

Concerning the architectural stimuli that evoke emotional responses (EC2, EC5, EC6), the most frequent features studied were color (66%), geometry (54%), and spatial organization (41%). Several articles, such as [45] and [53], showed how specific design elements-e.g., curved forms, natural lighting positively influence affective states, whereas asymmetric or cramped spaces can induce discomfort. However, there is a lack of standardization in protocols used to measure these effects, as evidenced by [34]. Therefore, developing unified, cross-cultural frameworks for emotion assessment in architecture is a necessary next step to ensure broader applicability.

In terms of methodological aspects and validation (EC10, EC11), the main weakness identified is the overwhelming focus on academic research settings (100%), with only 4% involving industry collaboration. The majority of contributions were based on experimental prototypes (58%), often tested in lab-controlled environments rather than real-world contexts, as observed in [18] and [40]. To address this, future studies

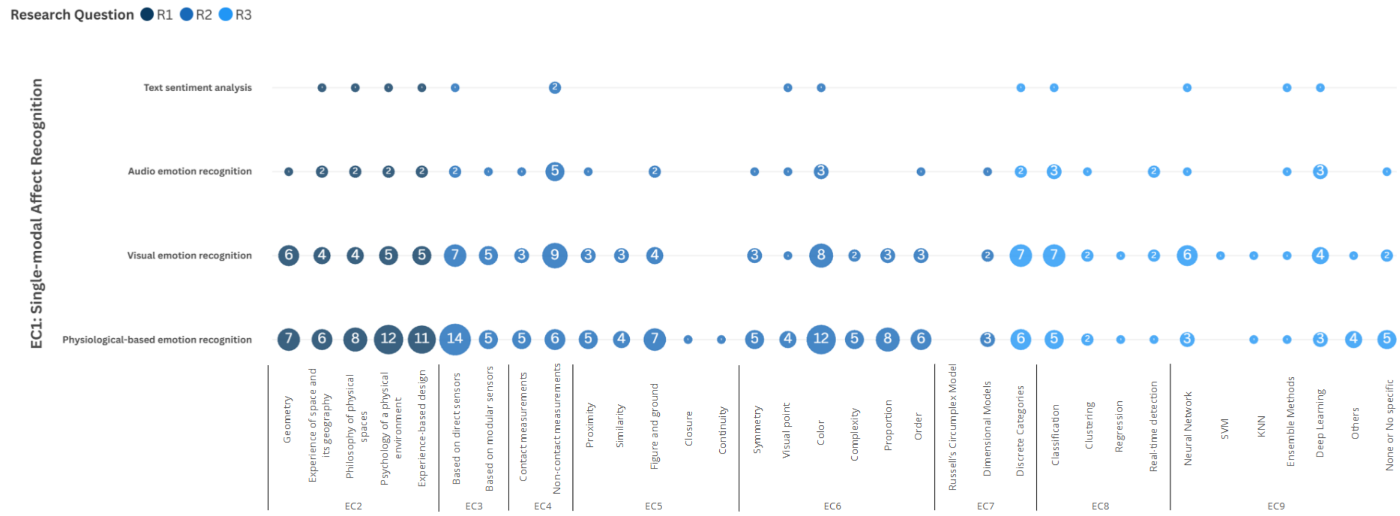

Fig. 1. Relation comparison between EC1:Single-modal Affect Recognition with EC2:Base Approaches to the Cognitive-Emotional Dimension of Architecture, EC3:Emotion recognition method based on measurement of electrical parameters, EC4:Emotion recognition method based on the measurement of non-electrical parameters,EC5:Perception and organization of elements, EC6:Psychological aspects applied to art, EC7:Models of emotion assessment, EC8:Function of the algorithm, EC9:AI Algorithms

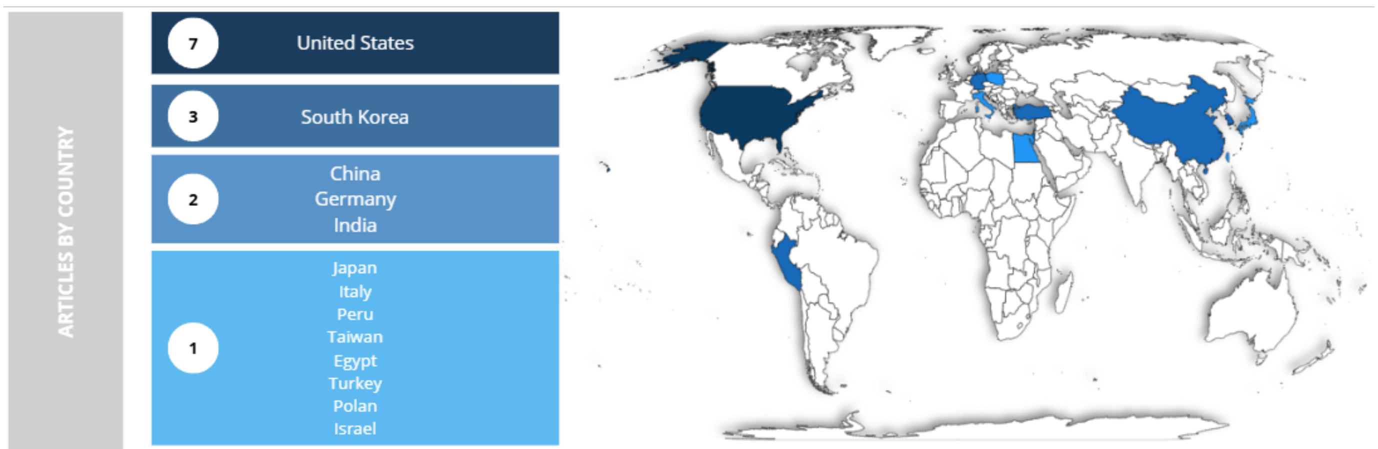

Fig. 2. Results by Country.

should strengthen partnerships between academia and industry and consider longitudinal field trials to assess the effectiveness of AI-driven adaptations in architectural environments.

Regarding data acquisition (EC3, EC4), physiological methods such as EEG and GSR were the most commonly employed (70%), while facial recognition systems (50%) emerged as promising non-contact alternatives suited for real-time applications. Nevertheless, non-electrical approaches like audio analysis remain underrepresented, suggesting an opportunity for integrating multimodal sensing to improve emotion detection reliability, as mentioned in [47].

As for the modeling of emotions (EC7), discrete emotional categories such as happiness and sadness were favored (50%) over dimensional models (16%) like valence-arousal. This preference reflects the practical orientation of design implementations toward actionable affective states. Notably, Russell's Circumplex Model was absent in the reviewed literature, suggesting a lack of engagement with more nuanced emotional representations that could better inform spatial interventions.

The strength of the main findings lies in identifying clear patterns between architectural design elements, emotional states, and AI-based recognition systems. However, the main

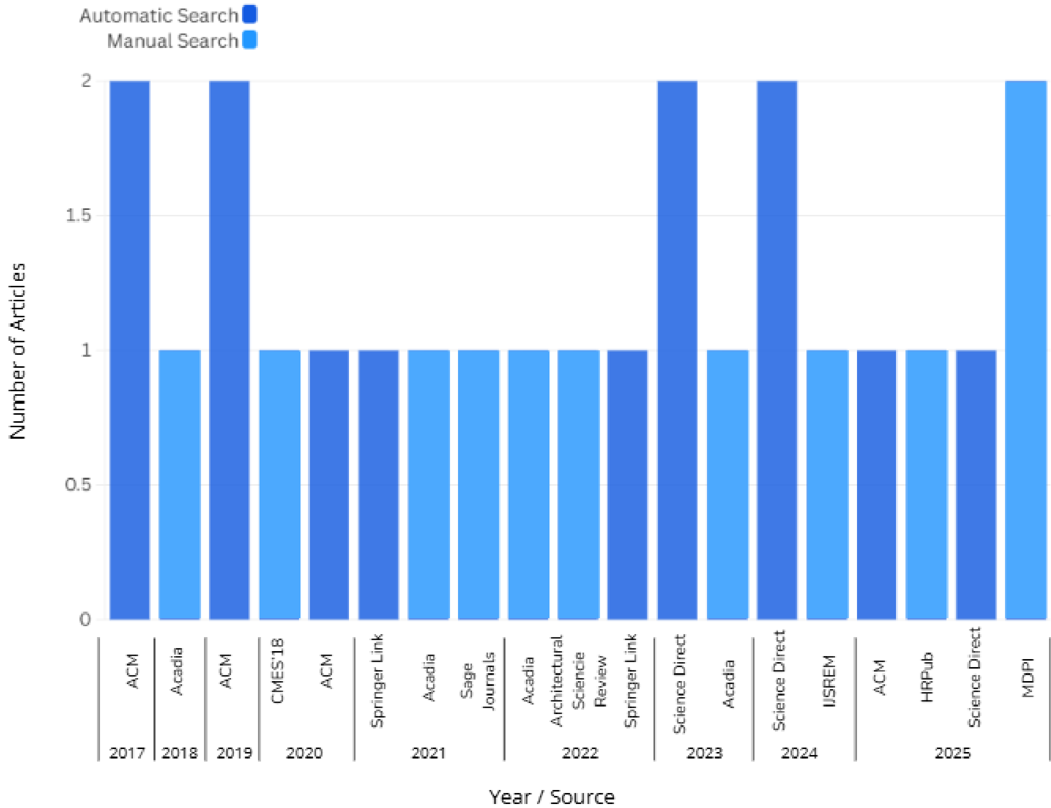

Fig. 3. Results by year, digital library and kind search.

limitations concern the lack of standardized validation methods, the minimal collaboration with industry, and the narrow focus on a limited set of emotional frameworks.

Finally, several future directions can be outlined. First, hybrid AI models that combine neural and traditional algorithms (e.g., SVMs, KNN) could enhance both classification accuracy and model interpretability. Second, it is crucial to develop standardized and replicable assessment protocols, as proposed in [34], to unify how emotional responses are measured in architectural spaces. Third, expanding research into industry applications, as seen in [15], can support the transition from prototypes to real-world implementations. Lastly, cross-cultural and longitudinal studies are needed to better understand emotional variability across demographics and over time.

VI. Validation of the Systematic Review

In order to support the methodological validity of the present study, specific procedures were carried out to verify the systematic literature review protocol and the data extraction strategy. In addition, an evaluation of the quality of the primary studies was carried out in order to guarantee the scientific soundness of the work, ensuring that the process was carried out accurately, exhaustively and as objectively as possible.

A. *Validation of the studies selection*

To secure the reliability and consistency of the study selection and data extraction processes, an inter-rater agreement analysis was conducted using Fleiss' Kappa statistic . This metric is widely employed in systematic reviews to assess the degree of concordance among multiple raters when categorizing items into discrete classes. The validation was carried out in two phases. In the first phase, a sample of 10 randomly selected studies—five of which were ultimately included in the review and five excluded—was evaluated by three independent researchers. Each evaluator independently judged whether each study should be included or excluded based on the predefined inclusion and exclusion criteria. The Fleiss' Kappa obtained for this phase was K = 0.783, indicating a substantial agreement among reviewers according to the interpretative scale proposed by Landis and Koch [**?**]. In the second phase, the consistency in data extraction was assessed. Each evaluator was assigned three studies already included in the review and asked to complete the findings matrix based on the predefined extraction criteria EC1 to EC8. The agreement was measured based on the binary presence 1 or absence 0 of each criterion per study. The Fleiss' Kappa obtained in this phase was K = 0.814, reflecting almost perfect agreement, thus confirming that the extraction procedure is being applied consistently and reliably across evaluators. These results demonstrate a high level of consistency in both the selection of primary studies and the data extraction process, supporting the internal validity of this systematic review.

B. Quality Assessment

To ensure the scientific relevance of the selected primary studies, a structured and reproducible quality assessment strategy was implemented. This assessment was based on three key dimensions: the quality of the publication venue, the academic impact measured through citation count, and the prestige of the dissemination channel, journal or conference). Each study was assigned a numerical score based on these criteria, allowing the review to maintain a high standard of evidence and comparability.

For journal articles, we employed the Scimago Journal Rank (SJR) system, which classifies publications into quartiles from Q1 to Q4. Studies published in Q1 and Q2 journals were awarded the highest score (10 points), while those in Q3 received 5 points, and Q4 publications received 0. Similarly, for conference papers, the CORE Conference Ranking was used, where conferences ranked A* or A received 10 points, as did those classified as B; conferences ranked C were awarded 5 points, and unclassified venues received no score. This dual classification system ensured a fair and consistent evaluation of publication quality across diverse formats.

To measure the academic impact of each study, citation counts were gathered from Google Scholar. The scoring model accounted for publication recency: studies published in or after 2020 with five or more citations received 10 points; studies with at least one citation, regardless of the year, were assigned 5 points; and studies with no citations received 0 points. This approach balanced the recognition of emerging research with the need to ensure a minimum level of influence in the field.

Each primary study received a total quality score by summing its venue score (journal or conference) and its citation score, providing a composite indicator of quality and impact. This composite score was used to prioritize studies during the data synthesis phase, ensuring that the most rigorous and influential works informed the conclusions of the review. On average, the studies included in this systematic review obtained a Paper Score of 7.69 and a Citations Score of 6.60, reflecting a generally high level of academic quality across the dataset.

This process was essential to maintain the integrity of the systematic review, allowing for the inclusion of studies that meet stringent criteria for scientific reliability, while minimizing the risk of bias or the influence of low-quality sources.

VII. CONCLUSION

This systematic review highlights the growing integration of artificial intelligence into emotion recognition within architectural design, a field that remains in an early but rapidly developing stage. The reviewed studies reveal a clear preference for neural networks and deep learning (29% each) to process multimodal data such as EEG, GSR, and facial expressions, enabling adaptive environments that dynamically respond to users' emotions. Architectural stimuli such as color, geometry, and spatial organization emerged as the most recurrent elements influencing emotional responses, with evidence showing how curved forms, natural lighting, and symmetrical compositions foster positive affective states, while cramped or asymmetric spaces can induce stress or discomfort. These findings underscore the potential of AI-driven methodologies to create human-centered, emotionally responsive spaces grounded in empirical evidence.

Despite these advances, several gaps remain that hinder the full maturation of the field. Most of the research is confined to academic contexts (100%), with minimal industry involvement (4%) and limited real-world validations beyond laboratory-controlled environments. There is also a lack of standardized protocols for measuring emotional responses, as well as a heavy reliance on discrete emotional categories (50%) rather than more nuanced dimensional models, which restricts the ability to capture complex emotional dynamics. Additionally, although visual and physiological modalities dominate emotion detection, non electrical and multimodal sensing techniques such as audio and behavioral analysis—remain underexplored, limiting the robustness and generalizability of current systems.

Future research should focus on bridging these gaps by fostering stronger collaborations between academia and industry, implementing standardized and replicable protocols for emotion assessment, and conducting longitudinal, cross-cultural studies that account for demographic and temporal variability. Developing hybrid AI models that combine neural networks with classical algorithms could enhance both performance and interpretability, facilitating broader adoption in practice. Ultimately, advancing these areas will accelerate the translation of AI-driven affective computing from experimental prototypes to scalable, real-world architectural applications, enabling spaces that not only meet functional needs but also actively promote emotional well-being and human flourishing.

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