Exploring EEG-based Design Studies: A Systematic Review

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Abstract

Background Human experiences are key considerations in design research and practice. Neuroscience techniques allow quantitative measurement of underlying human neurophysiological responses to design. However, despite the importance of electroencephalography (EEG) in performing such quantification, design experiments have not widely applied EEG, limiting the insights that design researchers can produce. Thus, this paper describes the use of EEG in experimentation in various design fields and suggests its integration into design research.

Methods This study systematically reviewed experimental design research that utilized EEG in various design domains, such as product design or architecture. Twenty-nine papers were selected using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) method. The selected papers were published in peer-reviewed journals between 2012 and 2022, written in English, and were analyzed for their design, variables, EEG tools and indicators, stimuli, experimental settings, analysis methods, and findings. Analysis was applied through a framework, population, intervention, control, outcome, and setting (PICOS) methodology.

Results This paper analyzed EEG-based experiments according to PICOS to provide information about how EEG is used in experimental design research, shedding light on the application of EEG methodology in various design fields, including product design, interior (or architecture) design, and service design. The results show that neuroscience techniques can be used to collect brain data for design research. EEG has been used in various experimental design research fields to explore how an individual user reacts to specific design elements and experience.

Conclusions Neurophysiological data retrieved from experiments can be used to develop evidence-based design strategies to improve the design process and design decision-making. The findings in this study contribute to our understanding of cognitive, emotional, and behavioral responses to design.

Keywords Electroencephalography (EEG), Experimental design research, Neuroscience, Design Neurocognition

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1. Introduction

Recent advances in methodologies and instruments to detect neurophysiological responses enable a design researcher to investigate cognitive functions (Hu & Shepley, 2022; Ball & Christensen, 2019). Brain responses have the potential to increase our understanding of the relationship between human behavioral response and design elements (Gero and Milovanovic, 2020; Vieira et al., 2020).

Specifially, electroencephalography (EEG) records brain electrical activity using electrodes placed on the scalp to capture brain waves from the frontal, parietal, temporal, and occipital cortex (Jaiswal,et al., 2010). Although EEG has considerable potential for deepening our understanding of how people respond to design elements, it has not been extensively applied in experimental design research. Accordingly, comprehensive information regarding application to design is lacking (Kim and Kim, 2022; Borgianni and Maccioni, 2020). A general conclusion about the relationship between EEG, design, and experimental research remains elusive.

This study reviewed and analyzed studies that included EEG as part of their experimental design. This paper further discusses the results of experiments measuring EEG in different brain regions and use of different EEG electrodes to measure neurophysiological responses to design-related stimuli. This study contributes to the extant literature by providing a comprehensive overview of previous EEG studies covering a wide spectrum of design domains.

This paper has three objectives: (i) to review the current research for EEG-based experiments in the field of design; (ii) to analyze the study design according to a population, intervention, control, outcome, and settings (PICOS) framework; and (iii) to discuss the limitations of current research and opportunities in future research.

2. Methods

The systematic review was conducted using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines by Moher et al. (2009). PRISMA is an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses and it primarily is used to evaluate the effects of interventions (Moher et al., 2009).

The scope of this review includes design research studies of EEG psycho-physiological signals. Table 1 identifies four categories consisting of key terms that reflect our review's objective. The selected keywords ensure the research objectives by adding synonyms and neighboring words. First, studies must involve EEG. Second, studies must adopt a biometric perspective within the analysis. Third, studies must be conducted in the design context; thus, terms identifying the field were grouped. Fourth, the experimental variable was specified to identify the human experience as the research focus. Using reliable databases, we aimed to apply our search terms only to article titles and abstracts. Scopus and Web of Science were utilized as online search databases to gather sources.

Table 1 Classification of Search Terms

	Type of Experiment	Biometric Perspective	Related to Design Research	Specification of Variable
OR	EEG	Biometric	Design	Preference
	Electroencephalogra*	Neurocognition	Interface	Feedback
		Neurophysiology	Product	Evaluation
		Physiological	Interior	Response
		Psychological	Architecture	Interaction
		Brain	Environment	Conception
		Cogniti*		Perform*
				Emotion
				Attention

Table 2 lists the eligibility criteria for the contents. Eligibility criteria for the studies included (a) written in English, (b) published after 2010, (c) available in full-text, and (d) peer-reviewed articles.

Table 2 Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Subject	Human	Non–human (i.e. animals)
Topic	Design–related	Not related to design (e.g. medicine, mathematics, pharmacology, biochemistry)
Method	Experimental	Non–experimental (i.e. observational, review, survey or interview)
Intervention	Design–related	Not related to design No comparators
Data		Not responding to the PICOS criteria Re–analysis of datasets from previous research Case study of EEG

The PRISMA flow diagram for the study selection process is depicted in Figure 1. The first identification phase consisted of studies retrieved from online databases via predetermined search strings. The initial search resulted in 10,457 studies from Scopus and 13,223 studies from Web of Science. However, 11,677 studies were excluded before screening due to publication limitations. In the identified articles, 15,678 are duplicates and were removed. In the next phase, inclusion and exclusion criteria in Table 2 were applied to titles and abstracts. A detailed full-text review of 192 articles was conducted to verify the eligibility criteria. Finally, twenty-nine studies were considered eligible for inclusion.

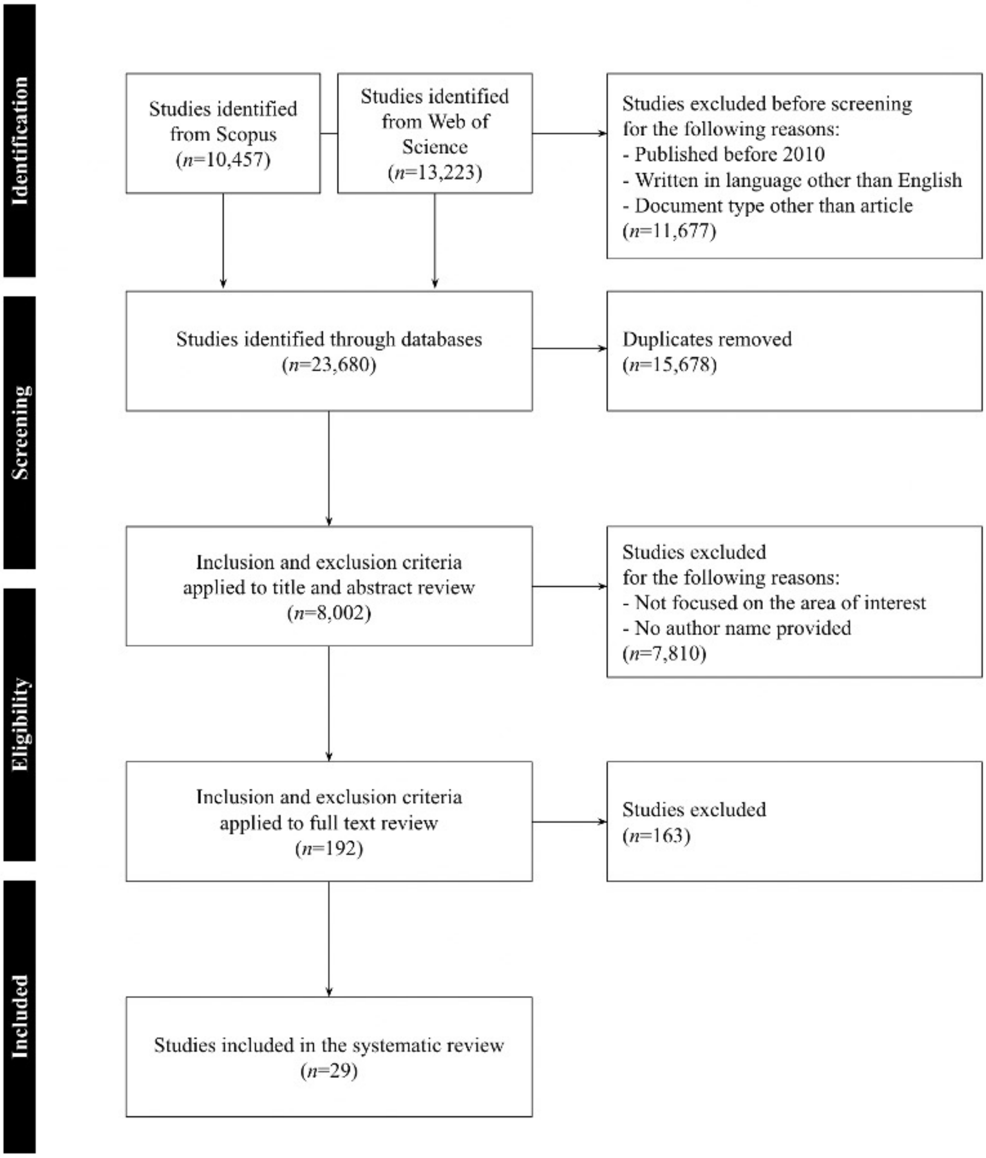

Figure 1 PRISMA Flow Diagram

This review adopted a framework for analysis utilizing the population, intervention, comparator, outcome, settings (PICOS) variation methodology by Higgins and Thomas (2019). Population (P) refers to participant charactersitics such as sample size, age, gender, and condition. Intervention (I) are variables being tested for and Comparator (C) are conditions of comparison within each group of independent variables. Outcomes (O) are the results of brain data retrieved from the EEG. Setting (S) refers to the controlled experimental conditions in the study.

3. Results

3. 1. Population

Participant sample sizes ranged from 8 to 160, with an average of 27. Regarding gender, seven studies did not specify gender; thus, they were excluded. In total, 53.5% of the participants were identified as males and 46.5% as females. The main role of participants was to evaluate the outcomes of participation in the design process and perform design tasks. Participant information is provided in Table 3.

Table 3 Participants

	Participants					
Author (Year)	Sample Size	M	F	Age Mean	Role	Condition
Al-Samarraie et al. (2019)	19	10	9	age range 20–23	Evaluator	Students who have not been to the UK and were unfamiliar with places in London
Alvino et al. (2021)	25	15	10	26.4	Evaluator	Mostly students and employees of the University of Twente
Aurup and Akgunduz (2012)	14	–	–	–	Evaluator	–
Cao et al. (2021)	21	12	9	26.7	Designer	Mechanical engineering postgraduate students at Sichuan University with at least 5 years of engineering experience
Clemente et al. (2014)	20	6 (1st group)	4 (1st group)	age range 22–29	Evaluator	1st group: viewed the environments by a common desktop screen 2nd group: viewed the environment on a power wall screen
		5 (2nd group)	5 (2nd group)	age range 21–29		
Deng and Wang (2019)	20	–	–	–	Evaluator	Students in the department of industrial design
Ergan et al. (2019)	33	22	11	age range 21–30	Evaluator	Students, faculty, and staff members at a univeristy campus
Guo et al. (2016)	14	7	7	25.4	Evaluator	Students from Northeastern University majoring in management science and engineering with a background of ergonomic
Guo et al. (2019)	26	16	10	25.1	Evaluator	
Hu and Reid (2018)	33	17	16	24.3	Evaluator	All from West Lafayette, Indiana 19: in an engineering program 14: in a non-engineering program
Khushaba et al. (2013)	18			38	Evaluator	
Kim et al. (2021)	33	0	33	30s: 26 40s: 7	Evaluator	Females who had used private rooms in postpartum care centers
Li et al. (2017)	15	0	15		Evaluator	Targeted consumer groups for the type of shirts
Li et al. (2020)	30	15	15	age range 18–25	Evaluator	University students

Liang et al. (2017)	12	6	6	age range 36–49	Designer	i. worked in the design industry in Taiwan for more than 10 years ii. responsible for leading design teams specializing in graphic and multimedia design iii. received awards in international design awards
Liang et al. (2019)	24	5 (novice)	7 (novice)	age range 20–23	Designer	i. junior or senior university students majoring in communication or design ii. achieved notable creativity and design performance levels
		6 (expert)	6 (expert)	age range 34–45		i. worked in the virtual experience industry for more than 10 years ii. being a renowned freelancer or having led design teams iii. received awards in international competition for interaction design
Liu et al. (2014)	24	–	–	–	Designer	–
Liu et al. (2018)	19	13	6	23.6	Designer	First-year graduate students from the School of Manufacturing Science and Engineering of Sichuan University
Llinares et al. (2021)	160	91	69	23.5	Evaluator	i. university student ii. have been born and be resident in Spain
Lou et al. (2017)	14	10	4	23.5	Evaluator	Postgraduate or undergraduate students majoring in mechanical engineering at Zhejiang University
Lou et al. (2020)	10	10	0	30.6	Evaluator	From Chinese elevator manufacturing company
Moon et al. (2019)	12 (1st session)	10 (1st session)	2 (1st session)	–	Evaluator	1st session: instructed to stand in front of the car
	4 (2nd session)	3 (2nd session)	1 (2nd session)			2nd session: instructed to watch the monitor screen
Naghibi et al. (2019)	11	5	6	26	Evaluator	Graduate students
Nguyen and Zeng (2014)	11			age range 25–35	Designer	Graduate students from the Quality System Engineering program at Concordia University
Nguyen et al. (2018)	8			age range 25–35	Designer	Graduate students from the Quality System Engineering program at Concordia University
Shin et al. (2015)	28	16	12	22.5	Evaluator	
Vieira et al. (2020)	84	46	38	35.5	Designer	Professional designers (23 mechanical engineers, 23 industrial designers, 27 architects, and 11 graphic designers)
Yilmaz et al. (2014)	15	5	10	22	Evaluator	
Zhang et al. (2021)	26	12	14	18–22: 14 23–25: 11 25<: 1	Evaluator	Students from Peking University

Lohmeyer and Meboldt (2016) classified evaluators and designers according to the participants' roles in the experiment to ensure that corresponding measures and analysis reflect the research objective. In the case of evaluators, the completed visual output was utilized as the stimulus. Whereas in the case of designers, cognitive ability during the design process is the measurable outcome along with their established experience as a comparator. The distinction between evaluators and designers continues to segment the studies' design area (e.g., product, interior, fashion, service, etc.), as shown in Table 4 and Table 5.

Table 4 Use of EEG in participant type: evaluator

Design Area	Design Subject/Element	Studies
Product	Wine labeling	Alvino et al. (2021)
	Automobile	Aurup and Akgunduz (2012)
	Bottle (Cultural element)	Deng and Wang (2019)
	Smartphone form	Guo et al. (2016)
	LED desk lamp	Guo et al. (2019)
	Cracker	Khushaba et al. (2013)
	Elevator	Lou et al. (2020)
	Automobile	Moon et al. (2019)
	Shoe	Yilmaz et al. (2014)
Interior/ Architecture/ Environmental Design	Level of luminance Presence of visual cues Presence of natural daylight Color of surfaces Openness	Ergan et al. (2019)
	Private rooms in postpartum care centers	Kim et al. (2021)
	Color hue of classroom walls	Llinares et al. (2021)
	Window shape	Naghibi et al. (2019)
	Ambient lighting	Shin et al. (2015)
	Environment (Open natural/Semi-open library/ close basement)	Li et al. (2020)
	Urban Street	Zhang et al. (2021)
Service	Virtual Environment	Clemente et al. (2014)
	Map	Al-Samarraie et al. (2019)
Fashion	Shirts	Li et al. (2017)
Engineering	Cyber-Physical System (CPS)	Lou et al. (2017)

Table 5 Use of EEG in participant type: designer

Design Area	Design Task	Studies
Design Process	Idea generation	Cao et al. (2021)
	Idea generation	Hu and Reid (2018)
	Verbalization of visual attention/association	Liang et al. (2017)
	Verbalization of conceptual imagination	Liang et al. (2019)
	Configuration and optimization	Liu et al. (2014)
	Problem-solving	Liu et al. (2018)
	Problem-solving	Nguyen and Zeng (2014)
	Problem-solving	Nguyen et al. (2018)
	Problem-solving and design sketching	Vieira et al. (2020)

The main path of the design process begins with considering potential users or evaluators. EEG is used in various experimental design research fields to capture evaluators' responses. In light of this exploration, specific design subjects or elements that lead to evaluators' appraisal are identified. The studies in each field had unique characteristics.

Product design studies ranged from automobile to daily consuer products. The influence of particular design outputs or specific elements of a particular design factor was assessed based on user preferences or emotions. Most such studies were conducted to determine whether their hypotheses about certain product variations were supported and used visual stimuli such as photographs or prototypes to show these variations. Alvino et al. (2021) elaborated on the influence of extrinsic cues in wine bottle labeling on consumers' visual attention. They assessed the implications of wine label designs on participants' brain activity using reaction times and EEG measurement. In consumer neuroscience, biometric measures are expected to provide an improved understanding of users' purchasing behavior. Guo et al. (2016) discussed the specific elements of smartphone products rather than a complete product. The presented stimuli consisted of colors, screen sizes, edges, and corners of smartphone design. Design studies addressing the influence of specific elements are expected to bridge the gap between evaluators' purchase behaviors and their unconscious cognition, which may not be addressed in self-rated questionnaires or interviews.

Interior design and architecture studies have mainly examined the relationships between people and spatial design elements, such as lighting, ceiling height, and wall color, on users' emotional and cognitive responses. Llinares et al. (2021) analyzed the effect of warm and cold hue classroom walls on university students' attention and cognitive memory function. They carried out an environmental simulation with 24 color configurations on the frontal and lateral walls of a virtualized university classroom. Kim et al. (2021) explored varied architectural elements of private rooms in postpartum care centers and the users' relaxation-arousal responses to each element were distinguished using the RAB indicator values of EEG.

In service design studies, the effects of user-controlled navigation on the sense of presence were evaluated while demonstrating the usability of the Emotiv EPOC headset (Clemente et al.,2014). Navigation control was tested with two evaluator groups according to screen types and visual stimuli conditions. Al-Samarraie et al. (2019) investigated users' performance locating a place of interest while utilizing a map. The symbolic and non-symbolic features in users' cognitive load was presented to determine the effectiveness of map visualization design. Unlike product design studies, service design studies have confirmed the significance of user experience while interacting with the product.

Whereas past design research has focused on participant roles as designers or evaluators, current studies have endeavored to encompass the design process. The design scheme evaluation method proposed by Lou et al. (2020) considers both experts' evaluation results and customers' psychological states.

3. 2. Intervention and Comparator

Indicators are concrete research constructs that provide evidence of the condition, behavior, or state (Lohmeyer and Meboldt, 2016). The form of visual stimuli applied to the most studies were photographs, which were used in 7 studies, although the photographs were of different types. For instance, Zhang et al. (2021) selected panoramic photographs of urban street scenes taken by a dual fisheye panoramic camera. They adopted visual pattern metrics to quantify and classify the visual stimuli and analyzed the correlations between three metrics:

percentage of landscape (PLAND), landscape division index (DIVISION), and Shannon's diversity index (SHDI).

Li et al. (2020) analyzed the connection between EEG data and subjective feelings, evaluating peoples' perceptions of architectural environments by measuring beta waves in the right temporal lobe. They exposed participants to virtual representations of an open, natural, semi-open library, and closed basement spaces while recording EEG data and compared this to participants' survey responses. Finally, they evaluated the relationship between subjective feelings and beta waves associated with work efficiency and spatial satisfaction.

Preferences are commonly measured to evaluate products and services. Significant changes in alpha waves can be observed in the frontal, central, occipital, and left temporal lobes in the Brodmann area. For example, Guo et al. (2019) asked participants to look at virtual lamp prototypes. They found that preference for lamps was positively correlated with alpha power, as detected by EEG in the frontal, central, parietal, occipital, left temporal, and right temporal regions of the brain. Table 7 summarizes intervention variables, comparators and stimuli.

Table 6 Intervention and Comparators

Author (Year)	Intervention Variable	Comparators	Stimuli
Al-Samarraie et al. (2019)	Map design charateristics	2 types (symbolic/non-symbolic)	Cartographic feature
Alvino et al. (2021)	Wine label selected according to hue and color, images, writings, bottle shape, and overall design	4 wine label designs	Photograph
Aurup and Akgunduz (2012)	Product feature alternatives	8 design features of automobiles (2 styles/features/2 colors/ background/aesthetic/style and features)	Photograph
Cao et al. (2021)	Design fixation	2 degrees of fixation (High design fixation level/low design fixation level)	Design tasks
Clemente et al. (2014)	Different levels of navigation control (the view of still photograph, the view of a video of an automatic navigation, free navigation through virtual environment)	3 levels of navigation control (Phtograph/video/navigation)	Photograph, Video, Virtual Environment
	Screen types	2 screen types (Common desktop screen/high-resolution power wall screen)	Screen size
Deng and Wang (2019)	Picture samples with different emotional states	6 pictures (cultural elements with different pleasure degree) Design sketch	Picture
Ergan et al. (2019)	Level of luminance Presence of visual cues Presence of natural daylight Color of surfaces and openness of spaces	2 virtual environments (the stress-reducing environment/ the stress-inducing environment)	Virtual environment
Guo et al. (2016)	Form features (screen size, color, edges and corners)	3 pairs (6 pictures in total)	Picture

Guo et al. (2019)	Visual aesthetic (Morphology, material, color)	3 visual aesthetic clusters consisted of 32 LED desk lamps (6 lamps of low visual aesthetic/17 lamps of neutral visual aesthetic/9 lamps of high visual aesthetic)	Virtual prototype (3D)
Hu and Reid (2018)	Personal context-specific experience	2 degree of contextual experience (novice designers,/expert designers)	Design tasks
Khushaba et al. (2013)	Shape (round, triangle, square), Flavor (wheat, dark rye, plain), Toppings (salt, poppy seed, plain)	57 choice sets (3 crackers that varied in shape, flavor and toppings)	Virtual prototype (2D)
Kim et al. (2021)	Architectural elements (aspect ratio of space, ceiling height, window ratio)	30 virtual settings	Virtual environment
Li et al. (2017)	Feature elements	7 feature elements of women's shirts (overall/neckline/shoulder/front skirt/ cuff/waist/sweep)	Product
Li et al. (2020)	Stroop effect/digital calculation/ meaningless figures recognition/ symbolic digital simulation	4 types of cognitive experiments	
	Open natural environment, semi-open library environment, closed-basement space	3 types of scenes	Photograph (Panoramic)
Liang et al. (2017)	Abstractness (Pablo Picasso), Surrealism (Joan Miro), Realism (Jean-François Millet)	18 Paintings (6 works from each artist)	Paintings
Liang et al. (2019)	Realism(Jean-François Millet), Abstractness(Pablo Picasso)	20 paintings (10 works from each artist) 2 levels of professionality (expert designers/novice designers)	Paintings
Liu et al. (2014)	Conventional NX interface, Game-based NX interface	2 User Interface Attributes	User interface
Liu et al. (2018)	Design problem statements	3 design problems (2 engineering design problems and 1 interior design problem) with 3 tasks each (open-ended/decision-making/constrained)	Design tasks
Llinares et al. (2021)	Color hue of classroom walls (warm hue, cold hue)	24 configurations (12 warm, 12 cold)	Virtual environment
Lou et al. (2017)	Product quality attributes	3 categories of product quality attributes (must-be/one-dimensional/ attractive)	Pictures, words
Lou et al. (2020)	Elevators with alternative design schemes	3 elevator design schemes	Product
Moon et al. (2019)	Sedans from different manufacturers (exterior design/interior design/ steering wheel design)	3 automobiles (3 scenes each)	Product, photograph
Naghibi et al. (2019)	Window shapes	16 window shapes (11 windows as pleasant/5 windows as unpleasant)	Virtual prototype (3D)
Nguyen and Zeng (2014)	Mental effort and mental stress during design problem solving	Open-ended design problems	Design tasks
Nguyen et al. (2018)	Design problems of variable difficulty	7 design problems (3 tasks per problem: sketching problem/multiple choice problem/subjective rating)	Design tasks
Shin et al. (2015)	Direct/indirect lighting (400lx downlight, 300lx uplight), direct lighting (700 lx downlight)	2 physical space	Environment

Vieira et al. (2022)	Constrained design task based on problem-solving/ Open design task based on design-sketching	2 types of design task	Design tasks
	Gender	Male and female	
Yilmaz et al. (2014)	Shoes with different styles and color	16 women shoes	Photograph
Zhang et al. (2021)	Visual patterns of urban streets (element, color, scale)	39 street scenes (3 spatial scales: 13 small/13 medium/13 large)	Photograph (Panoramic)

3. 3. Outcome

To study the role of biometric technology, in this case, EEG technology, the focus should be on the instruments and equipment employed throughout the experimental practice (Radder, 2009). From this perspective, Table 7 illustrates EEG hardware and software tools utilized in experiments. Five studies did not report the name of either the hardware or the software. Emotiv EPOC/EPOC+ is the most widely used EEG hardware, and MATLAB is the most commonly used software. Meanwhile, more than one software tool was utilized in 14 studies.

Past research has increasingly considered the relationship between psychological measures, theory, and design research methodology. Nguyen et al. (2018) highlighted the ongoing conceptual design process by focusing on the aspects of effort, fatigue, and concentration.

While concentrating on the design process of constrained and open design tasks, Vieira et al. (2022) discussed the effect of gender on EEG frequency bands. Gender was also included as a control variable in Zhang et al. (2021). Gender turned out to have a significant effect on the physiological indicators, but not on the subjective evaluations.

To evaluate perceptual responses to product design, Moon et al. (2019) used EEG and eye-tracking to strengthen the viability of the experiment. The study's finding demonstrated that perception of car design can be predicted via implicit monitoring based on EEG and gaze data (Moon et al., 2019).

Additional elicitation methods (i.e., survey, interview, video analysis, etc.) were employed in several studies to compare EEG signals with subjective evaluations and to identify biosignal indicators. Combining physiological and traditional methods (i.e., EEG and other subjective evaluation methods) is a preferred approach that can elucidate elusive dimensions of the human experience. Twelve studies applied different types of questionnaires. Nguyen et al. (2018) used NASA-TLX for the subjects to rate their workload. Lou et al. (2017) adopted Kano's questionnaire (Kano et al., 1984) that included functional and dysfunctional questions to explore psychological states to identify the achievement of a specific quality attribute. Zhang et al. (2021) pointed out the need for interviews or questionnaire since they found negative correlations between four out of six EEG indicators, even though the official algorithms of the Emotiv emotional indicator were adopted. Kim et al. (2021) found some similarities between EEG response and questionnaire results, based on which they suggested integrating self-reported assessments with EEG to further identify the relationship between psychological and physiological measurements. The reviewed studies primarily used questionnaires to verify the relationship between EEG signals and participants' subjective ratings.

Table 7 Outcome

Author (Year)	EEG Hardware Tool	EEG Software Tool	EEG Indicators/Brodmann Area	Variable	EEG Analysis Method
Al-Samarraie et al. (2019)	Emotiv EPOC	MATLAB	ERD (Event-Related Desynchronization) of alpha, theta and beta bands	Performance, Cognitive states	ICA, MARA (Multiple Artefact Rejection Algorithm)
Alvino et al. (2021)	EasyCap-62 channel cap, ActiChamp amplifier	BrainVision Recorder, BrainVision Analyzer	PCN (Posterior Contralateral Negativity) amplitude	Preference	ICA, ANOVA
Aurup and Akgunduz (2012)	ProComp2	BioGraph Infinity, EEG Suite, Minitab	Alpha peak frequency (F3 and F4)	Preference	Statistical (linear-trend line analysis)
Cao et al. (2021)	actiChamp-32 Research Amplifier	BrainVision Recorder, BrainVision Analyzer	Alpha band TRP (task-related power) changes in frontal, parietotemporal, occipital, and centroparietal	Fixation	MANOVA, Kruskal-Wallis ANOVA
Clemente et al. (2014)	Emotiv EPOC	EEGLAB	The innsula for the alpha and theta bands	Presence	SPSS, sLORETA, voxel-wise t-tests
Deng and Wang (2019)	EEG equipment (German Brain Products)	Brain Vision Recorder, Brain Vision Analyzer	Frontal lobe, the power of frontal alpha wave	Preference, Emotion	IGA, BPNN
Ergan et al. (2019)	14 channel EEG headset (Not further specified)	NR	Alpha, theta, beta oscillations across frontal channels	Stress, Anxiety	Power spectrum
Guo et al. (2016)	Neuroscan	Curry 7.0 SBA	N2, P2, and P3	Preference	ANOVA
Guo et al. (2019)	Neuroscan	Curry 7.0 SBA, MATLAB, E-Prime	Alpha and gamma power	Appreciation	ANOVA
Hu and Reid (2018)	B-Alert X10 headset	iMotions, Minitab	Alpha wave channel activation on F2, F3, F4, Cz, C3, C4, POz, P3, and P4	Performance, Cognitive states	ANOVA
Khushaba et al. (2013)	Emotiv EPOC	Emotiv Software Development Kit (SDK), MATLAB	Alpha, beta and delta across the frontal (F3, F4, FC5 and FC6), temporal (T7), and occipital (O1)	Preference	ICA, DWT, power spectrum
Kim et al. (2021)	EEG DSI-24	SWDSI-streamer, TeleScan	Alpha and beta wave frequencies, RAB (alpha/beta ratios) in the prefrontal (Fp1 and Fp2), frontal (F3 and F4), parietal (P3 and P4), and occipital lobes (O1 and O2)	Relaxation-arousal response	Wilcox signed-rank test
Li et al. (2017)	Emotiv EPOC	MATLAB	Not specified	Preference	ICA, DWT, descriptive statistics
Li et al. (2020)	EEG signal acquisition cap (Not further specified)	NR	Right temporal lobe, beta rhythm	Satisfaction, Work efficiency	Statistical regression, correlations
Liang et al. (2017)	Brain Rhythm EEG headset	EEGLAB	Frontoparietal, prefrontal, frontocentral, parietoocipital regions Beta power in channels Cz, F4, F8, Fz, FCz, F7, and FC3, Alpha power in channels Cz, F4, F8, Fz, FCz, F7, and FC3, Gamma power in channels, Cz, Pz, O1, FCz, C4, FT8, FC3, and FT7	Attention, Association	ANOVA, ICA

Liang et al. (2019)	EEG cap BR32S headset	EEGLAB	The right prefrontal in all frequency bands, the left temporal cluster, the right temporal cluster, the delta, theta, slow alpha, middle beta, high beta, and low gamma bands	Imagination	ICA
Liu et al. (2014)	NeXus-32	EEGLAB	Alpha peak frequency of the frontal lobe	Emotion	Fuzzy model, ICA, IIR
Liu et al. (2018)	actiChamp-32	BrainVision Analyzer	The alpha band in the frontal, parietotemporal, occipital regions of the right hemisphere, the theta and beta bands in the centrotemporal regions of the left hemisphere, the activations in the centroparietal and parietooccipital regions	Cognitive behavior	Descriptive statistics, ANOVA, ANCOVA
Llinares et al. (2021)	b-Alert x10	EEGLAB	The beta band (C3, CZ), the high beta band (F3, FZ)	Cognitive behavior (Attention and memory)	ANOVA, correlations, the Mann Whitney test
Lou et al. (2017)	EEG cap with 32 electrodes (Not further specified)	Neuroscan Nuamps amplifier, LIBSVM	Sample entropy	Needs	SVM (Support Vector Machine)
Lou et al. (2020)	EEG cap with 32 electrodes (Not further specified)	Neuroscan Nuamps amplifier, Curry 7.0	Sample entropy	Emotion	Cloud model, TOPSIS, ILPGWA
Moon et al. (2019)	Emotiv EPOC+	LIBSVM	PSD (Power Spectral Density)	Preference	ANOVA, ICA, correlations
Naghibi et al. (2019)	ANT Neuro ASA-Lab 64+8 ES	MATLAB, R software 3.4.2	The peaks of P3 and N1 in parietal and occipital channels, the peak of P2 in the frontal and central lobes	Emotion	Wilcoxon signed-rank, rank sum test, descriptive statistics
Nguyen and Zeng (2014)	Grass 15LT	In-house software system, MATLAB	Fpz, Fz, F4, F3, C4, C3, T4, T3, P4, P3, T6, T5, O2, and O1	Stress	Statistical tests
Nguyen et al. (2018)	NR	NR	Transient microstate percentage, alpha range, beta range, theta range, delta range, (theta+alpha)/beta, alpha/beta, (theta+alpha)/(alpha+beta), theta/beta	Effort, Fatigue, Concentration	RBF (Radial Basis Function) interpolatio, microstate clustering, correlations
Shin et al. (2015)	Quik-cap, NuAMP amplifier	MATLAB	Theta oscillations on the F4, F8, T4, and TP7	Emotion	paired t-tests
Vieira et al. (2022)	Emotiv EPOC+	MATLAB	Theta, alpha, and beta bands	Gender	Statistical tests
Yilmaz et al. (2014)	EEG 1200	MATLAB, in-house software	4Hz and 5Hz in the low frequency band, frontal channel on the left (F7-A1), temporal channel on the right (T6-A2), central (Cz-A1), occipital (O1-A1)	Preference	Statistical regression
Zhang et al. (2021)	Emotiv EPOC+	MATLAB	Utilization of EMOTIV performance metrics algorithms for cognitive states (Not further specified)	Emotion	Statistical tests

NR=Not Reported

As each biometric measurement is related to particular aspects of the human body, a deliberate application of various biometric measures supported by corresponding knowledge may support empirical data (Lohmeyer and Meboldt, 2016). Table 8 summarizes biosignals adopted by each study. For example, Lou et al. (2017) used EEG in the analysis, whereas the recorded EOG was only used to reject the artifacts. Eye-tracking and heart rate were the most utilized biosignals, along with EEG. Moon et al. (2021) included both EEG and eye-tracking signals to demonstrate the affective user experience of car designs. The eye-tracking analysis supported conclusions for two independent variables. Vieira et al. (2022) transformed fMRI tasks described in Alexiou et al. (2009) into EEG problem-solving tasks. Recent EEG studies have increasingly incorporated different biometric measures and adopted multimodal experimental tasks measured by other biosignals such as ECG, EDA, and heart rate.

Table 8 Biometric Measures

Author (Year)	EEG	ECG	EOG	Eye-tracking	EDA/GSR	Heart rate	Others
Al-Samarraie et al. (2019)	●						
Alvino et al. (2021)	●		●				
Aurup and Akgunduz (2012)	●						
Cao et al. (2021)	●						
Clemente et al. (2014)	●						
Deng and Wang (2019)	●						
Ergan et al. (2019)	●				●		PPG, EMG
Guo et al. (2016)	●						
Guo et al. (2019)	●			●			
Hu and Reid (2018)	●						
Khushaba et al. (2013)	●			●			
Kim et al. (2021)	●						
Li et al. (2017)	●			●			
Li et al. (2020)	●						
Liang et al. (2017)	●						
Liang et al. (2019)	●						
Liu et al. (2014)	●	●	●		●	●	EMG
Liu et al. (2018)	●						
Llinares et al. (2021)	●					●	
Lou et al. (2017)	●		●				
Lou et al. (2020)	●						
Moon et al. (2019)	●			●			
Naghibi et al. (2019)	●						
Nguyen and Zeng (2014)	●					●	
Nguyen et al. (2018)	●						
Shin et al. (2015)	●						
Vieira et al. (2022)	●						
Yilmaz et al. (2014)	●						
Zhang et al. (2021)	●				●	●	

3. 4. Settings

We found three different experimental environments in the EEG experiments: laboratory, field, and virtual. Correlation studies between EEG and human experience have been conducted predominantly in the laboratory, as the real world contains a wide range of external stimuli that may affect measurement. Kim et al. (2020) conducted an EEG experiment in a real-world environment and classified it as a field experiment. While the definition of field experiments may vary, the classification of field experiments and laboratory experiments remains elusive. Experiments with neuronal activity measures during controlled tasks can be considered field experiments since brain functioning is presumed to be a natural reaction to the controlled stimuli (Harrison and List, 2004). In this review, we defined a field experiment as a direct interaction between real-world products in an uncontrolled environment, which may include external factors of the surrounding. Lou et al. (2020) used a150 m high elevator test tower in the experiment. The participants took three different elevators with varying design schemes, and EEG data were measured while taking the elevator, which allowed us to classify it as a field experiment. In the case of Moon et al. (2021), the first session of the experiment was conducted in front of a car. Moreover, Moon et al. (2021) tried to verify whether a photograph can substitute for real products in two experimental sessions in which they compared perceptual responses induced by the photograph of a car and a real car.

Table 9 Settings

Author (Year)	Experimental Environment	
	Type	Conditions
Al-Samarraie et al. (2019)	Laboratory	Monitor
Alvino et al. (2021)	Laboratory	Computer screen (24-inch AOC G2460P LED computer)
Aurup and Akgunduz (2012)	Laboratory	17-inch monitor
Cao et al. (2021)	Laboratory	NR
Clemente et al. (2014)	Laboratory	Common desktop screen/Power wall screen
Deng and Wang (2019)	Laboratory	Computer screen (Presented by E-prime software)
Ergan et al. (2019)	Virtual	98-inch touch screen
Guo et al. (2016)	Laboratory	Computer screen (presented by E-Prime software)
Guo et al. (2019)	Laboratory	Monitor
Hu and Reid (2018)	Laboratory	Computer screen
Khushaba et al. (2013)	Laboratory	Computer screen
Kim et al. (2021)	Virtual	VR headset (HTC Vive)
Li et al. (2017)	Laboratory	NR
Li et al. (2020)	Virtual	VR integrated helmet (at a semi-circular dome experimental cabin with a radius of 2.4m)
Liang et al. (2017)	Laboratory	Slide show of prerecorded visual stimuli
Liang et al. (2019)	Laboratory	Computer screen
Liu et al. (2014)	Laboratory	NR
Liu et al. (2018)	Laboratory	Computer screen
Llinares et al. (2021)	Virtual	VR headset (HTC Vive)
Lou et al. (2017)	Laboratory	Computer screen
Lou et al. (2020)	Field	Elevators
Moon et al. (2019)	1st session: Field 2nd session: Laboratory	1st sesssion: Standing in front of the car 2nd session: Display on 84-inch LCD monitor
Naghibi et al. (2019)	Laboratory	S221HQLBD 21.5 inch LCD monitor
Nguyen and Zeng (2014)	Laboratory	Tablet
Nguyen et al. (2018)	Laboratory	Touchpad
Shin et al. (2015)	Laboratory	Experimental Room (4.7m x 4.4m x 3.1m)
Vieira et al. (2022)	Laboratory	Mauraria Creative Hub (University of Porto)
Yilmaz et al. (2014)	Laboratory	Fixed laptop computer (15-inch monitor)
Zhang et al. (2021)	Virtual	VR headset (HTC Vive)

NR=Not Reported

4. Discussion

4. 1. Limitations of current research

EEG has been used in various experimental design research fields, such as product, service, fashion, architecture, and engineering, to explore how participants react to specific design elements. However, studies in each field had unique characteristics and EEG measurements.

Architecture studies mainly examined the relationships of people and environmental elements, such as ceiling height, lighting, and wall color, with users'emotional and cognitive responses. This paper suggests identifying design elements, such as layout, furniture, and material that affect users' experiences of built and virtual environments. Product and packaging design studies examined user preferences for designs. Most such studies were conducted to explore certain product variations using photos showing these variations as stimuli. These studies' results can be used to create designs that cause certain emotional responses among consumers. Consumer marketing studies have examined the effects of visual marketing on relaxation, attention, and emotion utilizing EEG. They compared design elements, such as arrangement, colors, structures, and shapes of marketing features. Future research should explore how specific marketing techniques affect emotion and attention and whether these effects differ by delivery platform.

Experimental design studies based on EEG data are currently largely focused on evaluating how stimuli affect people's decision-making, opinions, and emotional responses. Most studies were conducted with participants outside the relevant research field to secure more representative data. However, limited EEG-based research has been conducted on designers' thought processes. In experimental design studies that feature EEG, participants complete tasks while their EEG signals are being recorded. Future research should be conducted to better understand designers' creative thought processes.

In data analysis methods, EEG data in current studies are limited to analysis using statistical tools. Future studies can be extended to develop classification and perdition models using machine learning algorithms to forecast individuals' cognitive, emotional, and behavioral patterns and preferences. Furthermore, it would be meaningful to further explore and discuss the relationship between anatomical activities such as Brodmann areas and cognitive effects during the thinking process. Future studies can explore the correlation between electrode placement across prefrontal, frontal, parietal, occipital lobe and correlate results with the Brodmann area and further interpret the meaning of differences in cognitive terms. Most current studies are limited to the use of EEG, which might affect the generalizability of the results. Further studies could combine EEG experiments with multimodal biometric tools, such as fMIR, ECG, EMG, GSR, and eye-tracking, as each tool is limited to measuring different human factors. This strategy can provide more comprehensive results. The mixed use of subjective interviews and surveys and objective methodology using biometrics can allow for cross-validation and clarification of results.

Our findings revealed a lack of investigations on how EEG can be used in design research on problem formulation or teams' perspectives. Rather than analyzing how perceptions of design are related to certain neural pathways, EEG channels, or Brodmann areas, most design studies have largely examined whether they could observe changes in brain signals to assess participants' preferences, stress, and simple emotional responses. Thus, design studies should use the EEG's capabilities more fully to investigate a continuous design process, rather than being limited to just evaluation and problem-solving. The analysis demonstrated the need to recognize design as a dynamic phenomenon and consider broader aspects of design research to integrate the multi-levels of design using EEG.
Experimental design studies on EEG channel indicators are limited. Even though each of the studies included in this study examined EEG channels, activated brain areas, and their related indicators, they did not produce consistent results about which behaviors were correlated with the activation of given brain areas due to the complexity of human cognition. Additionally, even though the studies were selected using a structured procedure, our decision to include a given paper was ultimately subjective. Non-design studies were excluded because we focused on how EEG is applied specifically in this field, which resulted in a biased sample.

4. 2. Future research agenda

Design research has developed as a multidisciplinary field. It incorporates biometric measures to gain further insights into human activities. Dinar et al. (2016) provided a systems-level view of the design process, encompassing major aspects of the design process. The cognitive process involved in the design activities align with the following levels.

Previously, the 29 identified EEG studies were classified based on the participant type of the experiment. In this respect, most studies were categorized into user, artifact, process, and designer levels. For instance, Guo et al. (2019) quantified the visual aesthetics of a LED desk lamp. The visual representation of the design was explored with the appreciation flow of evaluators (i.e., users). The elevator experiment of Lou et al. (2020) accounted for the ergonomics of artifacts. Navigation control was measured by Al-Samarrie et al. (2019) to illustrate the simulation and optimization model of the artifact, in this case, a map, which encompasses the design process.

Since the development of design research, many empirical studies have been conducted on virtually all aspects of design. However, EEG-based design studies have not explored to investigate multi-level perspectives (i.e., problem formulation, designer and teams, process, artifacts, and user) based on the framework of design (Dinar et al., 2016). Current studies are limited to evaluating artifacts or the design process. They have rarely identified problem formulation or group dynamics. Problem formulation or problem framing sheds light on the fact that designers are not limited to solving given problems, but need to further find and develop problems themselves (Cross, 2001). EEG has hardly been considered when trying to explore undetected problems. According to Dinar et al. (2016), the design field investigates teams to ensure their effectiveness (i.e., teamology) and interaction between members (i.e., group dynamics). As design is dynamic and intergrated, broader aspects must be considered in design research using EEG to incorporate the multi-level design.

5. Conclusion

In light of current developments regarding the intersection of design and neuroscience, this study conducted a systematic review of design studies using neurophysiological measures, especially EEG, to explore the responses of evaluators and designers. This study provides information about how EEG is used in experimental design research, shedding light on the application of neuroscience methodologies in various design fields, including but not limited to product design, interior (or architecture) design, and service design. The review indicated that neuroscience techniques can be used to collect biometric data for design research. Although biometric tools for neurocognition and neurophysiology have not yet been widely applied in design studies, further research should utilize such tools to understand design from an academic perspective. Currently, EEG research has focused mainly on determining how EEG can be used by examining the relationship between EEG data and data collected using traditional methods, or it focused on hypothesis testing. In both cases, EEG-specific experiments can provide evidence-based design.

In design research, EEG was widely used to study designers' cognitive and affective states (Zhao et al., 2020). EEG is used to measure neurophysiological activation while designing and problem-solving (Vieira et al., 2020). However, EEG studies to understand users' brain responses and design neurocognition to architectural environments are still at an early stage. Using advanced biosensing technology researchers can look at not only the built environment, but also investigate neurophysiological, physiological, and psychological responses in a virtual environment (Kim and Lee 2021; Mostafavi, 2021; Bower et al., 2019). Combining VR, EEG and body sensors has the potential to quantify human experience (Kim and Kim, 2022; Borgianni and Maccioni, 2020; Ergan et al., 2019). The implications of the findings can help architects and designers consider the effects of design elements to optimize user experience.

Future studies should be conducted with a wider definition of "design" as either a noun, which refers to creation of an entity, or as a verb, which refers to process or a series of activities (Miller, 2004). It is necessary to better understand the use of EEG in design research and its direct and indirect effects. Future studies can investigate the dynamic aspects of the design process and decision making. EEG-based design experimentation will offer more evidence-based insights in design research and practice.

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