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The Role of Engagement in Emotional Design

By

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Declaration

I hereby declare that, the contents and organization of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

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2022

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To the three generations of brilliant women in my family who, with love, effort, and resilience, forged the path that brought us here. This result belongs to all of you.

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Abstract

User engagement (UE) defines the link between a product and its users and measures whether users feel interested and involved. Identifying it correctly and selecting the most appropriate analysis method can provide meaningful information that could be used as input during the design process. Likewise, Emotional Design considers not only users' requirements but also their perceptions and reactions during and after an interaction with a product, service, or experience. In this sense, the literature regarding the technics for analyzing UE shows a higher prevalence of self-report over physiological methods, which implies an opportunity to include physiological metrics (electroencephalography, heart rate) and investigate further novel models to recognize if a user is more or less engaged.

For this work, a set of models, methods, and tools were selected to investigate the role of engagement. Specifically, Design Thinking (DT), the Technology Acceptance Model (TAM), electroencephalography (EEG), and heart rate are applied in selected contexts, such as e-learning, advertising, spaces design, and virtual environments.

The benefits of UE have been explored by deploying iterative methodologies conceived to increase users' involvement throughout the innovation process. As a first case, aiming at designing a more sustainable and viable solution, this work presents a conceptual design of the main sterilization chamber for infectious waste treatment obtained by DT deployment. Furthermore, considering that UE dimensions encompass users' attitudes and usage behavior toward new systems, TAM was selected, as part of this work, to analyze and define the determinants for successfully adopting an e-learning tool designed for EU farmers and agricultural entrepreneurs.

On the other hand, in view of the possibilities associated with physiological technics, the subsequent investigations are related to the search for a link between EEG and UE. For this purpose, three experiments were designed to explore if the EEG could assess the user's perception while interacting with a product/service. The first experiment aims to verify if an advergame creates a higher incidence in the UE, positively influencing user purchase intention (UPI). The second analyzes

using a VR environment, whether the forms and chromatic changes in the lightning condition can affect the users' emotions evaluated through their valence, arousal, and engagement. The third experiment, similar to the previous one, used EEG-based metrics to analyze the users' perceptions while exploring five VR scenarios conceived to elicit five particular emotions. Finally, an additional study regarding the use of heart rate as a means to understand student engagement is presented.

This work demonstrates the possibility of obtaining feasible results based on users' behavior analysis. Methodologies and models, such as DT and TAM, are characterized by their focus on the users and their capacity to include different stakeholders. By considering users' needs from the early stages of the design process, the results can be reflected in a better perception of the products and services offered and increased engagement. In addition, physiological technics provided reliable quantitative information to improve the emotional analysis and to frame users' feelings and perceptions while avoiding subjectivity in the responses.

The entire methodology was developed to support current research on emotional design. Each investigation contributed to the overall goal of providing solid evidence about the benefits of UE assessment and its role, including methods and tools for measuring and analyzing it during the design and development of a product, service, or experience.

This work intends to allow future researchers to consider the UE as one prominent indicator of product success and contribute to emotional design analysis. The obtained outcomes can be regarded as a potential foundation for future applications aiming to consider UE as a determining factor in their research.

Introduction

User engagement is a concept within emotional design that defines the connection between a product and its users and measures whether users feel interested in a product or service. It has been widely described as the process involving users through interactive experiences to create and enhance user-product relationships.

As user-product interaction has become increasingly important, users' engagement has become essential for developing competitive products, services, and experiences. Users' interest in a product does not depend anymore on a simple acquisition; they also want to live experiences and feel recognized. This evolving need requires the search for mechanisms and ways to connect more deeply with the users and gain knowledge about their inner perceptions while interacting with a product or service.

Researchers and practitioners can obtain this knowledge in various ways, which must be chosen according to their context, resources, and final purposes. Nevertheless, user engagement is a multifaceted metric with diverse measurement approaches; for this reason, one of the challenges is to outline how engagement can be measured and analyzed to enhance its potential benefits.

Many studies have aimed to quantify the users' engagement in fields like education, health, video games, marketing, arts, and social media, mainly through the use of traditional self-assessment methods; yet, recent technological advances have made possible the use of new technics to track and obtain information regarding the user's emotional state.

In light of the above, the principal purpose of this work is to analyze the role of engagement during the human-product interaction and how to take advantage of this indicator to enhance the product, services, and experience design.

For this reason, this work's methodology considers a chosen set of application fields and selected novel approaches; across its chapters, it will analyze and demonstrate different characteristics of user engagement expressions to offer a wide-ranging view of its applications, methods, and tools. Each chapter of this work

will focus on a method involving user engagement aspects during emotional design processes and provide evidence of its results.

The entire methodology was developed to contribute to current research on emotional design by providing solid evidence about the benefits of user engagement assessment. The peculiarity of this work is the inclusion of physiological methods and novel models to obtain reliable data to compare with the self-assessment reports, which are the common choice according to the literature. Likewise, the use of VR technologies as stimuli to induce specific emotions and offer the user a richer experience.

This work is structured beginning with a literature review summarizing the available metrics and techniques, including good practices of self-report methods and physiological approaches for measuring user engagement. The second chapter presents an industrial design of a sterilization chamber for infectious waste treatment through the concrete application of DT, a human-focused design approach that considers users' behaviors and needs to design products and services with which users will be more likely to engage. The third chapter investigates heart rate analysis as a physiological tool to measure students' engagement during online lessons. The fourth, fifth, and sixth chapters are the core of this work; these chapters explore a non-traditional method, specifically EEG, a technique for recording and interpreting the brain's electrical activity, to analyze users' engagement and, in addition, study valence and arousal as dimensions of emotion representation. For this purpose, three experiments were designed to assess the user's engagement while interacting with a product/service using EEG. The first experiment (fourth chapter) aimed to verify if an advergame generates a higher engagement response, positively influencing user purchase intention. The second (fifth chapter) analyzes whether the chromatic and form variations could affect the users' emotions evaluated through valence, arousal, and engagement using a VR environment. The third experiment (sixth chapter) aimed at exploring and validating the use of EEG as a means to understand emotions, using as stimuli the exploration of five VR scenarios conceived to elicit five particular emotions (happiness, disgust, fear, anger, sadness). Similarly to the second experiment, users' emotional response was evaluated in terms of variation of Engagement, Valence, Arousal, and Dominance.

Finally, the last chapter complements this work by including an investigation of the TAM to analyze the determinants that shape users' engagement and usage behavior toward a new e-learning platform conceived for the agriculture sector. The seventh chapter identifies the most commonly used external variables in e-learning,

agriculture, and virtual reality applications and proposes a new TAM extension; it concludes with the assessment of the technology acceptance through the validation of the extended TAM version previously proposed.

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Chapter 1

Towards an integrated framework to measure User Engagement with interactive or physical products

Building great products or services is not easy; users want products and services that exceed their expectations and evolve with their needs; it is not just about building the right features. Knowing the User Engagement (UE) towards a physical, virtual product or service can give valuable information that could be used as feedback for the design, enhancing its chances of success. In the context of user-centered design, UE is the assessment of the user experience characterized by the study of the individual's cognitive, affective, and behavioral response to some stimulus, such as a product, a service, or a website. UE considers not only the users' requirements and wishes but also their perceptions and reactions during and after an interaction with a product, system, or service. Many studies looking to quantify the UE are available. Still, a framework that provides a generic view of the most commonly used methods and metrics to measure UE does not yet exist in the literature. Aiming to understand the UE better, in this research, we developed a conceptual framework summarizing the available metrics and techniques used across different contexts, including good practices of self-report methods and physiological approaches. This chapter is intended to allow researchers, developers, and designers to consider UE as one of the most prominent product/service success indicators and use this guideline to find the more appropriate method, technique, and metric for its measurement.

1.1 Introduction

UE is an attribute of the user experience characterized by assessing the user's cognitive, affective, and behavioral investment when interacting with a digital system [1]. The UE can be interpreted as the level of involvement and absorption into an activity [2]. It has been widely defined as the process involving users through interactive experiences to create and enhance user-product relationships [3]. In this context, the product can be a physical or virtual object, service, or experience online and offline.

While developing a product, choosing carefully the most suitable methods to know the user's requirements and needs becomes an advantage [4], [5]. In this sense, User-Centered Design (UCD) is one of the most comprehensive methodologies and philosophies for designing interactive products. It enables the creation of valuable and usable products by significantly involving users in every stage of product development [6]. Following the UCD perspective, the UE considers not only the users' requirements and wishes but also their perceptions and reactions during and after an interaction with a product.

UE is a multifaceted, complex phenomenon with several potential and different measurement approaches [7]. However, it is an abstract construct that manifests differently within the whole spectrum of uses and applications; for this reason, one of the challenges is to define how the Engagement can be measured so that it can be used in design and evaluation. Studies have shown the necessity for a more context-specific approach when constructing measurement scales regarding the Engagement and the desire to obtain a set of items that allows measuring it in different sectors and natures [8].

Moreover, due to the variability of its application in different contexts and scenarios, an exact definition of “user” within the UE terminology is unclear. According to the various definitions of “user” and “consumer,” in this study, we use these terms as synonyms, considering the user as the final consumer of a product, service, or experience. For example, in education, the end-user is the student; in health services, is the patient; in the marketing area, the buyer; and in video games, the player.

All methodological approaches have advantages and limitations regarding UE use in specific populations and settings, and the measures may capture interactions subjectively or objectively [7]. As McNeal et al. [9] realized, performing direct UE

measurement and establishing associated metrics can be challenging. There are studies conducted in fields like education, health, video games, marketing, arts, and social media, among others. Still, one of the major gaps in the UE literature is the lack of evidence about how it should be standardized and measured [10].

Many studies have aimed to quantify the UE; however, a framework that provides a global and generic view of the different scales and methods used to measure it does not yet exist in the literature. After performing a literature review analysis, we found that most methods and metrics are classified into two main focuses: self-report or physiological. In this chapter, the term “physiological” describes the measurement done using a physical indicator and an associated instrument that depends on biological responses, for instance, measuring the students' engagement using electrodermal activity [2], [9] or heart rate analysis [11], or EEG signals [12], [13].

The methods and tools are widely varied; this opens new opportunities for evaluation and metric selection. Thus, with so many options for measuring UE, there is a need for an updated conceptual framework that summarizes the measurement methods and metrics and classifies them according to their parameters, tools/instruments, and context of use.

This chapter aims to provide a literature review regarding UE's most commonly used measurements and develop a conceptual framework of the current methods and metrics used for Engagement measurement. Specifically, this chapter addresses two objectives: first, to summarize the leading sectors and measures found in the literature. Second, to develop a conceptual framework that outlines the most commonly used methods and metrics, particularly physiological approaches, according to their application context. For this study, we use the definition proposed by Maxwell [14], who described the conceptual framework purpose as “clarify, explain, and justify methods” and later complemented by Burkholder et al. [15] as a theory or literature review that informs and describes the development of a research question, data selection and collection, analysis, and presentation of findings.

We expect this framework will allow future researchers to start from an initial state of the art, where the methods, techniques, and, whenever possible, the measurement scale used to measure UE would be easily found. Thus, this study's

perimeter offers guidance and a general scenario of the most commonly used methods, tools, and techniques.

This chapter is divided into the following sections. Section 1.2 sets the methodology used for the review process. Section 1.3 reports the literature review analysis, exploring the most frequently used methods according to their parameters. Section 1.4 includes the results contained within the framework, and in section 1.5, there are conclusions and discussion.

1.2 Method

Authors such as Schimanski et al. [16] and Dresch et al. [17] have made explicit the importance of the information flow in science research; therefore, for carrying out the literature review, we have followed the approach used by Motyl and Filippi [18]. In Figure 1, we have depicted the flowchart process used for our literature review.

For this research, the question posed is defined as follows, "What are the methods used to measure User Engagement?". Consequently, the search string used is as follows: (engagement) AND (measure OR measurement) AND (user OR consumer). The search was carried out in the Scopus DB and Google Scholar from years 2000 to 2020. Also, we have considered proceedings documents and additional sources such as Microsoft academics and Crossref. The following exclusion criteria were applied: duplicated records; documents not in English; documents written before 2000; and from the other sources, such as crossref, only documents with registered doi.

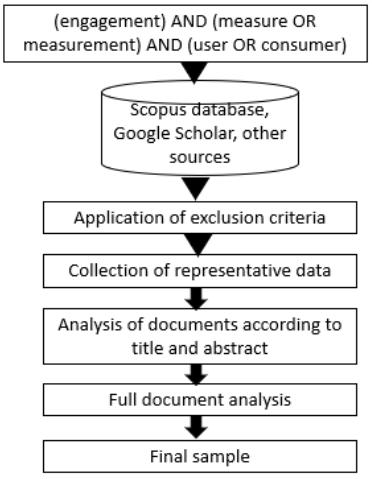


Figure 1: Literature review flowchart

The search protocol in Scopus DB and Google scholar initially matched 157 documents from 2000-2009, 229 documents from 2010 to 2015, and 512 from 2016 to 2022. It resulted in a total of 898 for the last 22 years and more than 600 additional documents from other sources. In Table 1, there is a summary of the document's quantity for each year set in the first step of the flowchart.

Table 1: Number of documents by year

	(2000-2009)		(2010-2015)		(2016-2022)	
	Papers	**Cites/year**	**Papers**	**Cites/year**	**Papers**	**Cites/year**
Google scholar	110	232	132	300	293	341
Scopus	47	112	97	229	219	238

After the initial match, we applied the exclusion criteria, obtaining 513 documents. Finally, after the abstract and full document analysis, the number of documents considered for this review was 386. After data analysis from the last 22 years, the numbers show an increase in the number of citations in this regard. The most influential articles had more than 300 citations in the last two decades. Particularly, between the years 2008 to 2010, the studies made by O'Brien and Toms [19], who developed a multidimensional qualitative scale to test the Engagement with software applications; Sprott et al. [20], who established an eight-item scale to measure the brand engagement and Brockmyer et al. [21] who created a questionnaire to measure the engagement in video game-playing, impacted the current research on this subject.

After the procedure illustrated in Figure 1, we classified the documents according to the method used, obtaining a collection of articles for each type (Table 2). Based on the results obtained, we found that most studies applied self-report methods to measure the UE, while others used physiological methods. Over the studies analyzed, we found that the most common methods used to measure UE using physiological tools are Skin conductance, Heart rate, EEG, Pupillometry, Posture analysis, Respiratory rate, and Facial expression.

Table 2: Classification of articles

		# Considered Articles
Self-report methods	Surveys, Interviews, and Questionnaires	63
		# Considered Articles
Physiological methods	Skin Conductance	31
	Heart rate	25
	EEG	41
	Pupillometry	30
	Posture	26
	Respiratory rate	28
	Facial expression	21

1.3 Review of User Engagement Methods and Technics

The literature review analysis shows that the UE measurement methods can be classified into two main groups, self-report and physiological. Many examples of good practices are available in the literature; according to these, the self-report methods can be categorized by approach (quantitative or qualitative) and type (interview, questionnaire, or survey). In addition, we have noticed that UE dimensionality was considered in many studies to describe and compare the self-report methods. Regarding the physiological methods, we have found seven approaches, as reported in Table 2.

Still, there is no evidence of a classification compendium for measuring the UE from the literature review. To fill this gap, in the following sections, we will explore the methods and technics most used according to the literature review analysis; our interest is to give an overview of the current UE methods to help researchers and practitioners quickly recognize the available methodologies for analyzing the engagement with a product or service. Table 3 shows an overview of the methods and parameters that will be reviewed in the following sections. Later, in section 1.4, the conceptual framework will contain the analysis results obtained during the reviews carried out for each type of method.

Table 3: Overview of UE Measuring Methods and Parameters

Type	Parameter	Description
Self-report methods	Self-report type	Questionnaire, survey, or interview
	Approach	Qualitative or Quantitative
UE Dimensionalities	Concept	Type of engagement used or identified
	Dimensionality	Multi or unidimensionality
	Dimensions	Sub-constructs that define a level of interaction.
Physiological methods	Physiological measurements	Skin conductance, Heart rate, EEG, Pupillometry, Posture analysis, Respiratory rate, and Facial expressions
	Measurement range period	Periods in which the measurement is performed
	Procedure for data analysis	Process used to measure the UE through the implemented method
	Engagement scales	Scale to measure the engagement used or identified
	Equations	Equations used to calculate or facilitate the UE understanding or classification

1.3.1 User Engagement self-report methods

Self-reported methods are assessments where users are asked to report their responses directly. Many standard measurements of attitudes, such as Likert scales and semantic differentials, are self-report. Similarly, constructs of interest to researchers, such as behavioral intentions, beliefs, and retrospective reports of behaviors, are often measured using this method [22], [23].

The self-report methods used to analyze the UE can be classified according to type or approach. Regarding the type, the studies typically used questionnaires, interviews, and surveys. Authors such as Lalmas et al. [7], Fredricks and McColskey [24], and Henrie et al. [25] have made significant contributions to the recompilation of self-report instruments.

The self-reports can also be categorized by the approach used (qualitative or quantitative); in this case, the classification is made according to the following criteria: quantitative, the instrument that includes numerical scales, and qualitative the instruments that do not contain numerical scales in its measurement.

From the literature review, considering these factors, the self-report type, the approach, and the context of the application (sector), we found numerous tools and methods to measure the UE. Many of these tools and techniques were created ad-hoc for each study, so the chances of standardization are low. However, some instruments are more frequently used. For example, the User Engagement scale (UES) [19] is one of the most used standard questionnaires since it aims to measure the quality of the user experience. The National Survey Student Engagement (NSSE) measures student participation in Canada and the United States concerning learning and engagement. At the same time, the Student Engagement Questionnaire (SEQ) [26] aims to capture student feedback and perception in a learning environment. In the field of task demand, the National Aeronautics and Space Administration (NASA) uses the NASA-TLX instrument as a subjective workload assessment tool to allow users to perform subjective workload assessments on the operator while working with human-machine interface systems [27]. The Game Engagement Questionnaire [21] identifies the user's psychological engagement when playing video games. Table 4 summarizes a collection of good practices using self-report methods for the UE analysis in different segments.

Table 4: Self-report UE measurement

Tool/Instrument	Self-report type	Sector	Approach	Reference
Student Engagement Questionnaire (SEQ)	Questionnaire	Education	Qualitative	[26]
National Survey of Student Engagement (NSSE)	Survey	Education	Qualitative	[28]
High School Survey on Student Engagement (HSSSE)	Survey	Education	Qualitative	[29]
Community College Survey of Student Engagement (CCSSE)	Survey	Education	Qualitative	[30]
NASA-TLX	Questionnaire	Task demand	Qualitative	[27]
Children's Engagement Questionnaire	Questionnaire	Education	Qualitative	[31]
Structured interview matrix (SIM) (For collaboration and engagement)	Interview	Community Resilience	Qualitative	[32]
Engagement Interview Protocol (EIP)	Interview	Immigration	Qualitative	[33]
Dundee Stress State Questionnaire (DSSQ)	Questionnaire	Psychological	Quantitative	[34]
Short Stress State Questionnaire (SSSQ)	Questionnaire	Task Engagement	Quantitative	[35]

Patient and family engagement (PFE)	Survey	Healthcare	Quantitative	[36]
Shirom-Melamed Vigor Measure (SMVM)	Questionnaire	Work	Quantitative	[37]
User Engagement Scale (UES)	Survey	Marketing	Quantitative	[19]
Utrecht Work Engagement Scale (UWES-9)	Questionnaire	Work	Quantitative	[38]
Game Engagement Questionnaire	Questionnaire	Video games	Quantitative	[21]
Affective Benefits and Costs of Communication Technology (ABCCT)	Interview	Communication technologies	Quantitative	[39]
Athlete Engagement Questionnaire (AEQ)	Questionnaire	Sports	Quantitative	[40]
Student Engagement in Schools Questionnaire (SESQ)	Questionnaire	Education	Quantitative	[41]
Engagement Questionnaire (EQ)	Questionnaire	Food	Quantitative	[42]
The Music use (Muse) Questionnaire	Questionnaire	Music	Quantitative	[43]
Music Engagement Questionnaire (MusEQ)	Questionnaire	Music	Quantitative	[44]
Student Course Engagement Questionnaire (SCEQ)	Questionnaire	Education	Quantitative	[45]
Game User satisfaction Scale (GUESS)	Questionnaire	Video games	Quantitative	[46]

Many UE studies have used almost exclusively self-report measurements; however, recent advances are making other types of evaluations more feasible. For example, self-reported outcomes can be contrasted to others that do not rely on respondents' reports, as physiological approaches that measure respondents' behaviors, sometimes in a constrained or controlled environment [23].

1.3.2 User Engagement Dimensionalities

Many researchers have explored the theoretical foundations as a systematic conceptualization of the UE [47], defining different types of sub-constructs or types of engagement [25], known as User Engagement dimensionality (UED), another way to compare self-report assessments [24].

UED describes the magnitude that captures a person's idea as a goal-oriented being equipped with a set of processes that guide their behavior in a changing environment. In other words, it is the level of interaction between a user and a product in a specific context; meanwhile, the user develops a perception that may or may not generate an engagement. The dimensions definition depends on the product; moreover, it depends on the potentially engaged user perspective.

From the studies' examination, it is possible to notice considerable differences in the dimensions that constitute the term *engagement* [48]. Two main

dimensionality groups emerged, defined as uni-dimensionality and multi-dimensionality; these groups allow the development and estimation of diverse theoretical and empirical models about how various characteristics of customer relations with a product impact the users' actions, behaviors, and intentions.

The uni-dimensionality is commonly expressed [47] as one of the three following engagement aspects: I) Emotional – Affective, II) Cognitive, or III) Behavioral. It retains the characteristic of simplicity and concept uniqueness, without extensive in-depth analysis and dimensions combination, in contrast to the multi-dimensionality that focuses dynamically on the three aspects defined previously. There is no agreement on the elements that should be primarily considered in uni-dimensionality or multi-dimensionality, but both provide helpful insights concerning the UE concept's appropriateness [49]. Furthermore, despite the number of studies supporting the UE's importance, there are still sharp controversies about its definition and the number of dimensions it includes [48], [49].

Furthermore, studies on UE must consider the characterization of the intended measure; in this regard, an important definition comes from Diamantopoulos and Winklhofer [50], who described the difference between reflective and formative measurements. Measurement development can focus on items composing a scale, perceived as reflective indicators of an underlying construct. Or, as an alternative measurement perspective, it could be based on formative indicators that involve creating an index of a weighted sum of variables rather than a scale.

The sub-constructs vary between authors and segments of application. However, we observed that the multi-dimensionality defined by Fredricks et al. [51] as Cognitive, Emotional, and Behavioral, and subsequently reviewed by Brodie et al. [47], Hollebeek [52], among others, is the most popular. Within the last five years, the research carried out by Dessart et al. [48] is particularly relevant to the topic; the study provides a classification of dimensional UE scales in the context of online brand communities. According to the literature review, it is possible to infer that the multi-dimensionality accomplishes better the principles that define the concept of UE because it includes a more in-depth analysis of user perception. Table 5 summarizes some examples of dimensional classifications for different segments based on and adapted from Brodie et al. [47], Hollebeek [52], and Dessart et al. [48].

Table 5: UE Dimensionality sub-constructs

Author(s)	Segment	Concept	Dimensionality	Dimensions/ sub-constructs
Achterberg et al. [53]	Psychology	Social Engagement	Uni	Social behavior
Jennings and Stoker [54]	Sociology	Civic Engagement	Multi	Media attentiveness, Trust, Political involvement
Fredricks et al. [51]	Education	School Engagement	Multi	Cognitive, Emotional, Behavioral
Algesheimer et al. [55]	Marketing	Brand Community Engagement	Uni	Motivational
Whelan and Wohlfeil [56]	Marketing	Brand Engagement	Uni	Behavioral
London et al. [57]	Education	Student Engagement	Multi	Academic investment, Motivation Investment, Commitment, Psychological connection, Comfort, Sense of belonging
Bejerholm and Eklund [58]	Psychology	Occupational Engagement	Multi	Daily rhythm of activity and rest, Variety and range of occupations, Place, Social environment, Social interplay, Interpretation, Extent of meaningful occupations, Routines, Initiating performance.
Bowden [59]	Marketing	Consumer Engagement process	Multi	Commitment, Development of trust, Involvement, Eventually affective commitment
Higgins and Scholer [60]	Marketing	Consumer Engagement	Multi	Cognitive, Emotional, Behavioral
Calder et al. [61]	Marketing	Online Engagement	Multi	Experiential, social
Sprott et al. [20]	Marketing	Brand Engagement in self-concept	Uni	Emotional / Affective
Gambetti and Graffigna [62]	Marketing	Engagement	Multi	Soft (relational), Pragmatic (Managerial)
Mollen and Wilson [63]	Marketing	Consumer Engagement	Multi	Active Sustained Cognitive Attention, Experimental value, Instrumental value
Van Doorn et al. [64]	Marketing	Customer Engagement Behaviour	Uni	Behavioral
Phillips and McQuarrie [65]	Marketing	Advertising Engagement	Multi	Engage to: Act, Identify, Feel, Transport, Immerse
Verhoef et al. [66]	Marketing	Customer Engagement	Uni	Behavioral
Fredricks and McColskey [24]	Education	School Engagement	Multi	Cognitive, Emotional, Behavioral
Brodie et al. [47]	Marketing	Customer Engagement	Multi	Cognitive, Emotional, Behavioral
Abdul-Ghani et al. [67]	Marketing	Engagement	Multi	Utilitarian, Hedonic, Social benefits

Wang et al. [68]	Education	School Engagement	Multi	First-order dimensions: A) Attention, Compliance. B) Belonging, Valuing. C) Regulation, Strategy Second-order dimensions: Behavioral (A), Emotional (B), Cognitive (C)
Hollebeek [52]	Marketing	Consumer Brand Engagement	Multi	Cognitive, Emotional, Behavioral
Vivek et al. [69]	Marketing	Consumer Engagement	Multi	Cognitive, Emotional, Behavioral, Social
Gambetti et al. [70]	Marketing	Consumer Brand Engagement	Multi	Experiential, social
Gummerus et al. [71]	Marketing	Customer Engagement	Uni	Behavioral
Cambra et al. [72]	Marketing	Customer Engagement	Multi	Commitment, Loyalty, Word-of-mouth
Vivek et al. [73]	Marketing	Consumer Engagement	Multi	Cognitive, Emotional, Behavioral, Social
Hollebeek and Chen [74]	Marketing	Brand Engagement	Multi	Cognitive, Emotional, Behavioral
Hollebeek et al. [75]	Marketing	Consumer Brand Engagement	Multi	Cognitive, Emotional, Behavioral
Baldus et al. [76]	Marketing	Online Brand Community Engagement	Multi	Brand influence, Brand passion, Connecting, Helping, Like-minded discussion, Reward (Utilitarian and Hedonic), Seeking assistance, Self-expression, Up-to-date information, Validation
Dessart et al. [48]	Marketing	Consumer Engagement	Multi	First-order level: A) Enthusiasm, Enjoyment. B) Attention, Absorption. C) Sharing, Learning, Endorsing Second-order level: Affective (A), Cognitive (B), Behavioral (c)
Hollebeek et al. [77]	Musical	Musical Engagement	Multi	Social identity, Transportive experience, Affect-inducing experience
Violante et al. [78]	VR Design	Consumer Engagement	Multi	First-order level: A) Enthusiasm, Enjoyment. B) Attention, Absorption. C) Sharing, Learning, Endorsing Second-order level: Affective (A), Cognitive (B), Behavioral (C)

1.3.3 Physiological methods

Body language is a more reliable and authentic form of transmitting information than verbal communication [79]. Without realizing it, the body continually sends information about intentions, feelings, and behaviors. Even without verbal expressions, the physiological factors speak for the body and can be very significant.

During the development process, to create a successful product with higher positioning and differentiation [80], it is crucial to choose the most appropriate method to understand the user requirements [4], [5]. For these reasons, as anticipated in Table 3, we have classified the existing physiological methods used to measure the UE level with a product according to: the type of physiological measurement, measurement range period (time in which the measurement is performed), the procedure for data analysis (process used to measure the UE through the implemented method), engagement scale (used or identified scale to measure the UE), and the equations used to calculate or facilitate the UE understanding and classification.

The reviewed physiological methods are: Skin conductance, Heart rate, EEG, Pupillometry, Posture analysis, Respiratory rate, and Facial expressions. These methods will be further described in the following sections.

1.3.4 Skin Conductance

Electrodermal activity (EDA), also known in the literature as skin conductance response and galvanic skin response (GSR), are terms used for defining the continuous autonomic variation in the electrical properties and characteristics of the skin. It can reveal the humans' physiological arousal, connected to a subject's attention and alertness, and is considered a suitable approach for measuring the UE during different tasks, stimuli, or situations [2], [9].

GSR includes a slow variation or tonic component known as the skin conductance level (SCL) and the skin conductance response (SCR). The tonic component SCL is interrupted by increased skin conductance due to a particular stimulus [9]. Studies have used a variety of sensors to measure the variation in the electrical properties and characteristics of the skin. For example, Morrison et al. [81] and Di Lascio et al. [2] used the Empatica E4 wristband galvanic sensor; this sensor allows to record the skin conductance variation measured in μSiemens in a specific time interval and report the user experience. The task could be split into three main periods to guarantee a good measure of the skin conductance variation [2], [81]–[84], as can be seen in Figure 2a:

- Relax period to obtain a baseline recording
- Task development period
- Recovery period

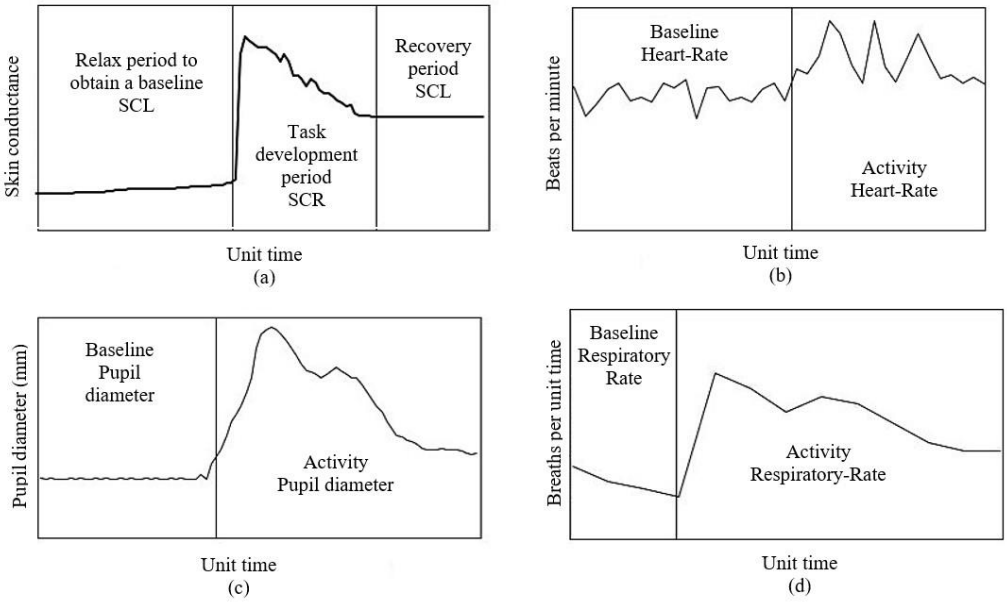


Figure 2: Physiological time intervals. (a) Skin conductance variation. (b) Heart rate data graph. (c) Pupil diameter data graph. (d) Respiratory rate data graph

After filtering the data, it is possible to plot the variations (on the vertical axis, the Skin conductance measured in μSiemens, and on the horizontal axis, the unit time). In this order, it is possible to identify the three periods. It is important to note that every user will have specific data, and every plot will have different variations according to the type of activity measured; consequently, it is difficult to generalize the UE level.

For that reason, and because the GSR signal is highly individual-dependent and can vary a lot from user to user [85], [86], several studies [2], [83]–[85], [87], [88] carried out normalization of the skin conductance data, comparing the users' skin conductance during the task development against their baseline recording. In order to counteract this dependency, the following normalization is typically used [89] (Equation 1):

$$\Phi ix = \frac{SCL(ix) - SCL\,(\min)}{SCL(max) - SCL(\min)} \tag{1}$$

- Φix Indicated the normalized value
- SCL (ix) Indicates the current value
- SCL (min) Indicates the minimum value
- SCL (max) Indicates the maximum value

After normalizing the entire signals (rather than just the tonic component), it is possible to generate a general comparable data graph, as shown in Figure 3.

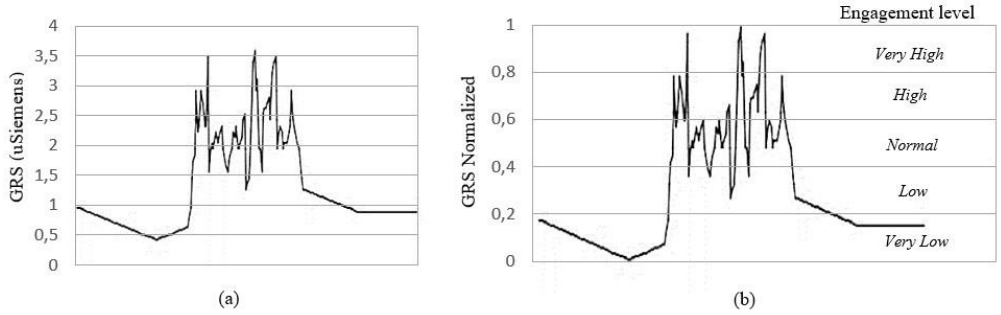


Figure 3: (a) Original skin conductance data graph. (b) Standardized data graph

Finally, Di Lascio et al. [2] stated that the level of UE in skin conductance could be measured using the normalized graph by dividing the different levels of skin conductance into five groups:

- Very high engagement between 0,8 and 1
- High engagement between 0,6 and 0,8
- Normal engagement between 0,4 and 0,6
- Low engagement between 0,2 and 0,4
- Very low engagement between 0 and 0,2

1.3.5 Heart rate

Heart rate (HR), known as pulse, is the number of times a person's heart contracts per minute; these contracts vary from person to person according to age, weight, body size, heart conditions, medication, and performed activities [22].

HR is highly susceptible to variations due to the emotions and reactions of the subject; for that reason, different authors have used this physiological characteristic as a measure of UE. Previous studies have identified and confirmed that the HR and the level of engagement to a task relate to the HR variation during an activity development; this, because a person's heartbeat reflects emotional levels and reactions [11], [22], [90]–[92]. Furthermore, the HR tends to increase when the user is experiencing strong emotions and tends to decrease in an immersive environment [93], [94].

The method to identify the engagement of a user using the HR [90], [94]–[96] can be generalized by separating the measure results into two stages (similar to GSR), the first to set the HR baseline and the second to measure the corresponding HR during the development of an activity as can be observed in Figure 2b. After data filtering, the HR can be analyzed graphically in two ways: the first one analyses the HR using a graph where the vertical axis corresponds to the beats per minute (BPM), and in the horizontal axis, the unit time; in this way, it is possible to identify the increases and decreases peaks in the HR measured periods. The second method calculates the HR variability (HRV) according to the alterations in the time interval between consecutive heartbeats in milliseconds. To measure the HR, the authors have used a wide range of trackers, and the selection depended on the type of study performed and the required accuracy.

Authors like Darnell and Krieg [11] proposed a linear regression of the recorded data to establish the variations throughout the activity execution, concluding that there is an HR decrease in comparison to the initial one, except for the fortuitous stimuli that can be due to factors internal or external to the test. Richardson et al. [91] proposed a data normalization to remove any baseline difference in the user data and verify the variation more concisely.

Consequently, depending on the type of activity, the engagement can be represented either by an HR increase or decrease, resulting in high variations in the general population's results. For example, Rooney et al. [97] identified a reduction in the HR in a short film immersion but increased attention. At the same time, during lectures, Darnell and Krieg [11] concluded that there are increasing and decreasing HR variations that can characterize attention changes. Due to this discrepancy, we can conclude that the UE level will depend on the variation of the HR with respect to the baseline identified in the first measurement step; the interpretation made based on this indicator must consider that the results will vary from subject to subject, and according to the application context. More reflective environments intended to engage the user will tend to have a stable HR variation. In contrast, active environments with many stimuli will have a more significant HR variation concerning the baseline.

1.3.6 Electroencephalography

EEG is a test that measures the electrical activity of the brain. It is typically performed by placing electrodes on the scalp to detect the electrical activity of the brain cells. This activity is then displayed on a monitor as brain waves, which can

be used to diagnose various neurological conditions. The test is non-invasive, and painless. According to the user's state, the brain's nerve cells generate electrical impulses that fluctuate rhythmically in different patterns. The electrical EEG signal is composed of different frequencies produced by neuronal electrical activity; these frequencies, known as bands, are classified as Delta(δ), Theta (θ), Alfa (α), Beta (β), and Gamma(γ). Each type of band reflects specific and different cognitive processing skills in particular brain areas [98]. Furthermore, studies have validated that EEG can provide metrics for determining task engagement and arousal [12].

As well as GSD and HR, the EEG measurements regarding UE can be divided into two phases [12], [98], [99]; the first consists of baseline data to control the initial subject response. The second phase contains the electrical brain activity measurement while carrying out a task. For EEG measurements, a range of instruments are available in the market like the neuroSky MindWave, OpenBCI 3D printed devices, traditional Ag/AgCl electrodes, Neuron spectrum 1, and one of the most used in the last years, Emotiv EPOC [12], [100].

For the location of the electrodes, the studies typically used the 10-20 electrode placement system, as McMahan et al. [12], while using the Emotiv EPOC device, as well as, Nuamah and Seong [101]. In this system, each electrode has one or two letters to identify the lobe or brain area as follows: Pre-frontal (FP), Frontal (F), Temporal (T), Parietal (P), Occipital (O), Central (C), and includes the Z (zero) reference (FPz, Fz, Cz, Oz), see Figure 4 for reference.

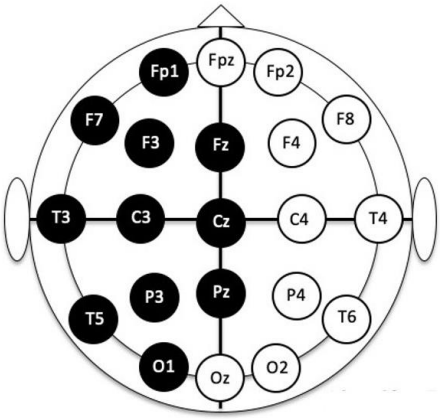


Figure 4: 10-20 system electrode placement

Studies using EEG have identified different engagement indexes. Kang et al. [102] used the Neural Engagement Index (NEI), and Yamada [103] defined the frontal middle theta rhythm as a valuable index of attention. In the study carried out by Pope et al.[13] and confirmed later by Freeman et al. [99], the authors developed an EEG-based engagement index (Equation 2), considered to be the most effective among different studies [12], [98], [100], [104], [105], this because this index reflects task engagement in a more precise and validated way. Furthermore, studies have shown that EEG-based indexes are reliably linked to various levels of decision-making tasks.

$$Engagement\ Index = \frac{Beta\ (\beta)}{Alpha\ (\alpha) + Theta(\theta)} \tag{2}$$

Pope et al. [13] classified the frequency bands as Theta (4–8 Hz), Alpha (8-13 Hz), and Beta (13-22 Hz). The theta waves describe a lower mental activity (resting state), while alpha waves are related to lower mental alertness, this one appears in a sleep-wake cycle. In contrast, Beta waves describe a higher mental activity, system activation, and alert state of the brain; in other words, Beta waves are related to an increase in brain activity during a task and allow the identification of attention changes due to external stimuli, indicating cognitive processes and changes in brain states while performing a task [105].

The EEG engagement index, in Equation 2, identifies the UE level by comparing the initial user state with the stimulus responses; if it increases, a higher engagement is expected [12], [13], [98]. In this way, it is possible to identify the user engagement or disengagement with an activity, considering the baseline period versus the EEG data while performing a task.

1.3.7 Pupillometry

The pupil diameter analysis has been recognized for many years as a psychophysiological arousal index [106], [107]; pupil dilatation is related to a certain level of engagement during the performance of an activity [108] and a function of processing load or mental effort required to perform a cognitive task [109].

According to various authors [108]–[113], for the measurement, two periods during the test can be established to confront the data, one to define the baseline of the pupil diameter and the other for the measurement during the activity development. It is possible to plot the total variation of the pupil diameter or just

the variation concerning the baseline data, as depicted in Figure 2c. Also, it is essential to consider that the baseline pupil diameter gradually reduces when the user begins participating in a task [109], [114].

The measurement time for each period depends on the study. For example, authors like Jepma and Nieuwenhuis [113] for the first period identified that the pupil data during the 0,5 seconds immediately preceding the task could not be included as a baseline period because the user presented an anticipatory increase in the pupil diameter, while Murphy et al. [115] used the mean pupil diameter over the 500 ms pre-stimulus as a baseline.

In the last years, authors have used different specialized instruments, like the Tobii eye-tracker 2150, brain vision analyzer, iView X MRI-SV eye-tracker, among others. To eliminate artifacts and blinks, authors [112]–[114] commonly used a linear interpolation algorithm.

The data analysis is correlated with the time-on-task and difficulty[107], [109], [110], [112], showing that the pupil diameter is more significant when a difficult task is presented, reaching a peak that specifies an engagement point. Kassem et al. [116] suggest that the presence of arousal stimuli induces a dilatation of the pupil, confirming a rise around the moment of the stimuli independent of the baseline [117].

Podder et al. [118] proposed an engagement behavior function (EB) according to a Graph-Based visual saliency (GBVS) while presenting a video. This method is divided into two steps: in the first one, this model forms activation maps on individual feature channels and then normalizes them in a way that highlights conspicuity based on human visual perception and attention (Equation 3).

$$EB = f\left(PS_L, PS_R, F, \frac{1}{D_A}, \frac{1}{D_G}, \frac{1}{D_C}, \frac{1}{D_E}\right) \quad (3)$$

In the function, all the variables have the same weight to create a ranking between the subjects in the study, proving the worst and best level of performance that can represent the concentration/engagement level. The variables' descriptions are the following:

- The left pupil size (PS_L)
- Right pupil size (PS_R)

- Blinking pattern (F)
- Distance between an individual's average gaze location to all participants' average gaze location as obtained by the eye tracker data (D_A)
- Distance between an individual's average gaze location to the average gaze location as predicted by the GBVS model (D_G)
- Distance between an individual's average gaze location to the center of the videos (D_C)
- Distance between an individual's average gaze location to the most significant points, according to the video experts (D_E)
- Pupil sizes are measured in mm, blinking patterns in percentage, and gaze distances in pixels.

It is possible to conclude that the level of engagement depends on the pupil diameter variation in relation to the baseline. Additionally, Gilzenrat et al. [112] verified that increases in baseline pupil diameter would be associated with decreases in task utility and disengagement from the task, although reduced baseline diameter (but increases in task-evoked dilatations) would be related to task engagement. Besides, Equation 3 is a valid approximation of the UE level between users of the same study group.

1.3.8 Posture

Posture is the most natural element to observe and interpret within nonverbal communication [119]. Posture is a primarily involuntary signal that can be involved in the communication process. Although it seems to go unnoticed, the brain receives and processes the information, often unconsciously, and responds automatically to a stimulus; for this reason, it is crucial to measure how the posture of a subject can indicate whether a user is engaged or not.

According to the literature, various systems for measuring posture have been developed, usually indicated as Body Pressure Measurement System (BPMS) and Sitting Posture Monitoring System (SPMS) [120], [121]; both systems look to identify the position of the user according to a reference system.

The most popular method to measure engagement evaluates the subject's posture (while solving a task seated) using pressure sensors located in the chair. Mota and Picard [119] and D'Mello and Graesser [121] used two pressure sensor matrices located at the seat pan and in the seat's backrest. Shirehjini et al. [122] decided to embed the sensors in the chair, having a non-invasive system allowing the subject to adopt a normal seated posture reproducing real-life conditions; as

well as Bibbo et al. [120] have done, using a chair equipped with eight analog tactile pressure sensors. The difference between authors is the location where the sensors are placed in the chair; Table 6 contains some examples of sensor locations.

Table 6: Sensor location examples

Posture classification				
Mota and Picard [119]	Shirehjini et al. [122]		Bibbo et al. [120]	
Leaning Forward	Sitting on the edge of the seat	S1	All	P1
Leaning Forward Left	Sitting Upright	S2	OverLapRightBack	P2
Leaning Forward Right	Slumping back	S3	OverLapLeftBack	P3
Sitting Upright	Loose	S4	OverLapRight	P4
Leaning Back	Leaning Left	S5	OverLapLeft	P5
Leaning Back Left	Leaning Right	S6	SeatAll	P6
Leaning Back Right	Right leg on left	S7	SeatFront	P7
Sitting on the edge of the seat	Left leg on the right	S8	SeatFrontBackUp	P8
Slumping back				
	Pressure sensors location			
Two matrices of pressure sensors are located at the seat pan and backrest. 64 integrated pressure sensors	Eight sensors are embedded in the seat and back of the chair		Chair equipped with eight analog tactile pressure sensors, four in the seat and four in the back.	

A graphic example of these locations (Figure 5) is the one used by Bibbo et al. [120], a study that shows adequate results.

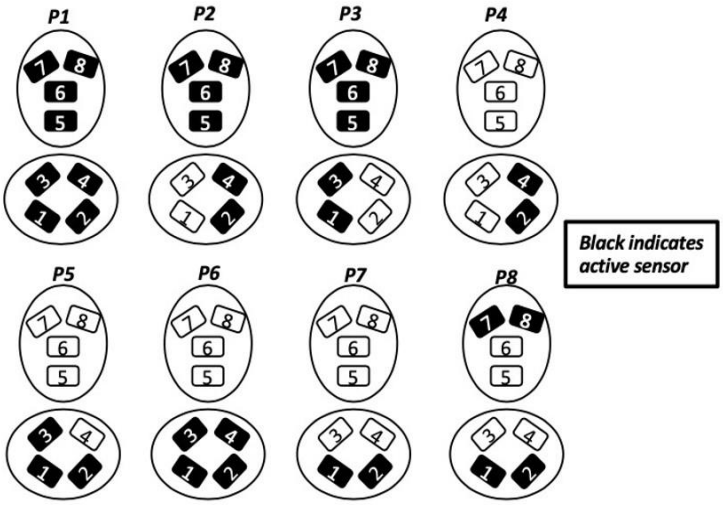


Figure 5: Posture Classification

Regardless of the pressure sensor used, the studies [119]–[122] conclude that a high level of UE exists when there is increased pressure on the chair seat with minimal movement and when the user tends to lean forward on the chair trying to get a better focus in the task [120]. On the other hand, a low UE level (disengagement) is identified when there are rapid changes in the pressure on the chair's seat and when the users have a significant distance between their face and the screen or activity [121], [123].

D'Mello and Graesser [121] used the BPMS produced by Tekscan to examine the pressure map during an emotional stimulus (called frame), finding three significant pressure-related functions: the average pressure (μ), the average coverage (C), and the average coverage change in a pressure mat ($a_{coverage}$). These functions are represented in Equation 4. R is the number of rows in the pressure matrix, C is the number of columns, and P_{ij} the pressure of a sensing element in row i and column j.

$$\mu = \frac{1}{R \times C} \sum_{i=1}^{R} \sum_{j=1}^{c} P_{ij}$$

$$C = \frac{1}{R \times C} \sum_{i=1}^{R} \sum_{j=1}^{c} X_{ij}$$

$$a_{coverage} = \frac{1}{N}\sum_{i=1}^{N}|C_t - C_{t+1}|$$

$$\begin{aligned} X_{ij} &= 1, \quad if \quad P_{ij} > 1 \\ X_{ij} &= 0, \quad if \quad P_{ij} = 0 \end{aligned} \tag{4}$$

The elements contained in Equation 4 allows the BPMS system to efficiently identify pressure features to facilitate the measurements and better understand the results. In conclusion, regardless of the system used, the changes in the subject posture measured with pressure sensors can indicate the level of UE when performing a task. Specifically, the user is engaged when they tend to lean forward, exerting higher pressure on the seat.

1.3.9 Respiratory rate

Respiration is a way to consciously influence our physical and emotional responses, reflect feelings, relate to the environment, and impact the body's general state. It is a factor that reflects emotional response [124]. Its variability is an indicator of mental stress and sustained attention to a particular task [125]; therefore, it is considered a physiological factor that can measure the level of the UE.

According to several authors [125]–[128], and following the same procedure used in other physiological methods, the users' respiratory data is generalized in two stages, the first to set the baseline, the second during the development of the activity; in this way, it is possible to contrast the initial data with its variation (see Figure 2d).

There are different types of instruments for measuring respiratory rate. For example, Webster and Colrain [127] used a mouth-breathing mask. Wenger et al. [128] used a respiratory pneumotachograph to measure the respiratory volume. Gomez et al. and Vlemincx et al. [129], [130] used a respiratory inductive plethysmograph to measure the rate and volume of each breath; and Vlemincx and Luminet [131] used two respiratory belts around the chest and the abdomen, besides making use of a breathing face mask.

According to the research, respiratory data, unlike the other physiological methods for measuring the UE, has not been a leading research method [129]. Only

a few authors have analyzed this physiological factor and its relations with UE when performing an activity.

Vlemincx et al. [130] proposed some main respiratory parameters (Equation 5) to measure respiratory variability, breath by breath, including Respiratory volume (Vi), Respiration Rate (RR) and Minute ventilation (MV).

$$RR = \frac{60}{Total\ breath\ time} \qquad MV = \frac{RR}{Vi} \tag{5}$$

Existing studies [124], [125], [128]–[130] demonstrate that random breathing variability increases during mental stress, difficulty, or excitement; and decreases with task-related attention. Also, the respiratory intensity during different emotional states varies according to the type and duration of the stimulus.

1.3.10 Facial Expressions

Facial expressions are the changes that occur in our faces as a response to inner emotional states. In this sense, the UE analysis using facial expressions (no verbal communication type) aims to identify facial manifestations and their direct relationship with emotions. The facial expression analysis encodes and interprets the facial muscle movements to determine the internal emotional reactions. These reactions can be a rich source of social signals conveying the user's focus, attention, intention, motivation, and emotion [132].

Different studies have identified the importance of the time scale for recognizing facial expressions. Nezami et al. [133] used in their research three time-scale types: an entire video projection, a 10-second video clip, and single images. This time scale allowed them to categorize the facial expressions manually using labels and annotations to analyze and classify them according to a scale to rate the user status. This process is challenging due to inconsistencies between labelers/annotators, hence the need to automate this kind of process [134].

The literature review shows different computer-vision techniques to automate the UE analysis with a product. Several methods/architectures make it easier to analyze facial recognition, such as the Boostbf, Support Vector Machine (SVM), and the CERT Toolbox [134]. One of the most used is the Convolutional Neural Network (CNN) [133], [135], [136], a deep learning algorithm trained to recognize and classify facial expressions according to a preestablished facial data set.

The engagement scale parameters using facial expressions vary according to the study. For example, Whitehill et al. [134] defined it as I) Not engaged at all, II) Nominally engaged, III) Engaged in a task, and IV) Very engaged, Nezami et al. [133] defined it as I) Engaged and II) Disengaged, and Ramya et al. [137] defined it as I) Like, II) Dislike and III) Favorite. The main difference between studies that use CNN is related to the dataset used to train the network. For example, Nonis et al. [135] used the Bosphorus public database, Nezami et al. [133] used the dataset from the facial expression recognition challenge 2013, and Zhang et al. [136] combined temporal information with spatial information by applying CNN's to recognize facial expressions.

The study by Nonis et al. [135] shows adequate results regarding the relationship between facial expression and UE with a product. The study used an Intel® RealSenseTM SR300 and MobileNetV2 instruments and trained the network using the Bosphorus public database, then classified the engagement into three classes according to Russell's circumplex model of affect as follows: I) Deactivation: low engagement level with relaxed and calm expressions, II) Average: medium engagement level with happy, contented, serene and elated expressions, and III) Activation: high engagement level with alert and excitement expressions.

Olivetti et al. [138] also applied this classification while analyzing UE during the interactions with a virtual environment using a Support Vector Machine (SVM) method to classify the engagement level according to the analysis of the facial expressions. Likewise, Violante et al. [139] used an SVM, and Russell's circumplex model of affect, generating three classes to define the inner users' requirements: I) Deactivation, II) Pleasure, and III) Arousal.

It is possible to conclude that the analysis and recognition of facial expressions is an effective physiological method to identify the UE level with a product, mainly because of the adequate results found using CNN trained with a facial dataset. The classification of the UE used by Nonis et al. [135] can be used as a reference to identify the user status.

Finally, Table 7 shows a general guideline of the physiological methods discussed in this section, including the parameters of range period measurement, metrics, the procedure for data analysis, engagement scale, and equations.

Table 7: Physiological methods for measuring UE

Method	Measurement range periods	Metrics (Y-axis vs. time)	Procedure for data analysis	Engagement scale	Equations
Skin conductance	1) Relax period (Baseline) 2) Task development period 3) Recovery period	µSiemens	Normalization (Φix) of the skin conductance data compared to the user skin conductance during the task development against their baseline and recovery recording.	According to the normalized data [2] • Very high engagement Φix between 0,8 and 1 • High engagement Φix between 0,6 and 0,8 • Normal engagement Φix between 0,4 and 0,6 • Low engagement Φix between 0,2 and 0,4 • Very low engagement Φix between 0 and 0,2	$\Phi ix = \frac{SCL(ix) - SCL\ (\min)}{SCL(max) - SCL(\min)}$ Where: Φix Indicated the normalized value $SCL(ix)$ Indicates the current value $SCL\ (\min)$ Indicates the minimum value $SCL(max)$ Indicates the maximum value [89]
Heart Rate	1) Rest Heart Rate (Baseline) 2) Task development period	BPM or HRV	Compare the user's Heart rate during the task development against their baseline recording.	The engagement can be represented by a heart rate increase or decrease depending on the activity.	
EEG	1) Subject regulated measure period (Baseline) 2) Task development period	EEG engagement index	Extract frequencies for each band, calculate each period's EEG index and compare the index.	The EEG index identifies the engagement level when it increases compared to the baseline index; a higher EEG index means a higher engagement level.	$EEG\ Engagement\ Index = \frac{Beta\ (\beta)}{Alpha\ (\alpha) + Theta(\theta)}$ Frequency bands: Theta (4–8 Hz), Alpha (8-13 Hz), and Beta (13-22 Hz) [13]
Pupillometry	1) Initial Pupil Diameter period (Baseline) 2) Task development period	Pupil diameter or pupil diameter dilatation (mm)	Compare the user's Pupil diameter or dilatation during the task development against their baseline recording.	Increases in baseline pupil diameter would be associated with decreased task utility and disengagement from the task. In contrast, reduced baseline diameter (but increases in task-evoked dilatations) would be related to task engagement.[112] It is possible to calculate an engagement behavior function (EB) [118]. A higher EB function indicates a higher engagement ranking. All the variables have the same weight to create a ranking between the	$EB = f(PS_L, PS_R, F, \frac{1}{D_A}, \frac{1}{D_G}, \frac{1}{D_C}, \frac{1}{D_E})$ PS_L and $PS_R$are the left and right pupil size measured in mm, F is the blinking pattern, D_A is the distance between an individual's average gaze location to all participants' average gaze location as obtained by the eye tracker data, D_G is the distance between an individual's average gaze location to the average gaze location as predicted by the GBVS model, D_C is the distance between an individual's average gaze location to the center of the

				subject in the study that allows demonstrating the worst and best level of performance that could represent the concentration/engagement level according to the study carried out.	videos, and D_E according to the experts, the distance between an individual's average gaze location to the most significant point.[118]
Posture	1) Initial Posture period (Baseline) 2) Task development period	Pressure level	Compare the initial user posture during the task development against their baseline posture.	It is possible for mat pressures using the BPMS to calculate the average pressure (μ), the average coverage (C), and the average coverage change in a pressure mat ($a_{coverage}$) [121] When the user tends to lean forward, exerting higher pressure on the seat, they are engaged.	$\mu = \frac{1}{R \times C}\sum_{i=1}^{R}\sum_{j=1}^{c} P_{ij}$ $C = \frac{1}{R \times C}\sum_{i=1}^{R}\sum_{j=1}^{c} X_{ij}$ $a_{coverage} = \frac{1}{N}\sum_{i=1}^{N} \lvert C_t - C_{t+1} \rvert$ Where R refers to the number of rows in the pressure mat, C the number of columns, and P_{ij} is the pressure of a sensing element in row i and column j $X_{ij} = 1, \quad if \quad P_{ij} > 1$ $X_{ij} = 0, \quad if \quad P_{ij} = 0$
Respiratory Rate	1) Rest Respiratory Rate (Baseline) 2) Task development period	Breaths per unit time	Compare the Respiratory user rate (RR) during the task development against their baseline rate.	During mental stress, difficulty, or excitement, a random breathing variability (RR) tends to increase and tends to decrease with the presence of task-related attention	$RR = \frac{60}{Total\ breath\ time}$ $MV = \frac{RR}{Vi}$ Respiratory volume (Vi), Respiration Rate (RR), Minute ventilation (MV) [130]
Facial Expression	1) Task development period	Depth map in output from the 3D sensor	Using the trained Convolutional neural network (CNN) with a facial dataset is possible to classify the engagement level according to a defined scale.	*Classes*: Deactivation; Average; Activation *Engagement level*: Low; Medium; High *Expressions*: Relaxed, Calm; Happy, Contented, Serene, elated; Alert, Excitement Engagement scale, according to based on Russell's circumplex model of affect [135].	

1.4 Results

UE has been validated as an approach that integrates design objetives with users' inner requirements. Moreover, fields like manufacturing, engineering, virtual reality, and any technical discipline must consider the user's feelings and reactions toward an expected output during the first design steps; in other words, a wrong

decision during the design process would affect the manufacturing operations directly. The design of a product and its formal specification must be combined with behavioral and organizational theories to develop an understanding of the user needs, contexts, and possible solutions [140].

We have realized that no document in the literature provides a generic view of the different methods and metrics used to measure UE. Thus, we aim to offer insights and guidelines for any design discipline that intends to implement UCD methods and apply UE as feedback for its analysis.

The results of this conceptual framework, summarized in Table 8, derived from three analyses: the first one concerned the self-report methods, the second related to the conceptual definition of the UE through its dimensionalities, and the last one focused on the physiological methods.

Table 8: Conceptual framework content

Framework reference	**Method**
Self-report UE measurements (Table 4)	Questionnaire Survey Interview
UE Dimensionality sub-constructs (Table 5)	Uni-dimensionality Multi-dimensionality
Physiological methods (Table 7)	Skin conductance Heart rate EEG Pupillometry Posture analysis Respiratory rate Facial expression

The findings verify that the UE is defined and measured differently depending on the application context; yet, getting to know better the engagement level of a user with the product under analysis can give valuable information that could be used as feedback for the design process, enhancing the chances of success of a product. In many aspects, the focus and extent of the analysis performed will create a product that users wish to interact with [80]. For that reason, we have included examples of good practices in this framework.

This study identified several authors who have conducted significant studies on self-report methods and their characteristics. For future studies on this topic, we see opportunities for research related to identifying and standardizing a methodology

based on UED sub-constructs to complement the development of self-report instruments.

Referring to physiological methods, in the literature, we found different physiological approaches for conducting the UE measurement; in the framework, we have included the most commonly used. From the revision, we concluded that there are no standardized scales since the measurements are highly dependent on the conditions under which the studies are carried out. Consequently, the standardized scales for some physiological methods, such as heart rate, pupillometry, posture, and respiratory rate, are still a research gap. A common scale could be beneficial, facilitating the measurement and guaranteeing a clear understanding of the results. In this sense, there is an opportunity for future studies interested in this topic that wish to focus on less-used physiological methods for measuring the UE.

Most existing studies on UE focus their goals on determining the engagement value using a parameter explicitly created for their research. In this way, finding lessons learned and guidance from other studies could become difficult due to the lack of standardized methods. The available literature review documents analyzed a particular UE domain and referred to a specific application context. For example, in the study conducted by Pontes et al. [141], the authors made a systematic literature review of the instruments used to measure political engagement. The Handbook of Research on Customer Engagement [142] is a good source of information regarding exclusively marketing practices and organizational performance. Kulikowski [143] explored the literature on work engagement as a predictor of health. Furthermore, Bazzani et al. [144] presented an overview of EEG application in consumer neuroscience, briefly discussing the drivers of engagement.

Some evaluated studies concluded the need to adopt physiological approaches to assess engagement. Current studies on UE do not necessarily focus exclusively on one field; thus, considering this framework as a starting point for further research can give a global vision of the most commonly used methods in different fields and help the reader delimit their research area.

The best method to use will depend on many factors; so far, the previous studies are making considerable progress on physiological technics, analyzing the physical user responses to a stimulus, and obtaining a reliable engagement value. These findings demonstrate that the inclusion of physiological characteristics provides

information that allows the researcher to determine whether the findings from self-reports are trustworthy and representative; however, the sample size is much lower compared to traditional self-report methods, limiting the generalization of the results.

On the other hand, self-reported methods have been in the UE context for more time, and it is usual to find validated instruments for specific fields. It is also essential to consider resource availability, budget, time, and experience. In the case of physiological methods, we realize that the equipment needed is much more expensive than self-reports, and the researchers must follow a considerable training period to collect and evaluate reliable data. Fortunately, recording equipment is getting relatively cheaper and more user-friendly; that is the case, for example, of the new EEG headsets available on the market.

The findings from this framework suggest the need to apply a mixed UE measurement technic using self-report and, whenever possible, a physiological method to validate the results. In addition, there is a need for an agreed conceptualization of UE measurement; future studies from the same contexts should try to address their finding as an input to create a standardized UE measure. The information in this framework could then be used as the basis to explore already validated methods and, based on them, develop reliable UE measurements.

Through a review of the different methodologies, the framework developed in this chapter provides a comprehensive summary of current evidence obtained through an objective and transparent approach to minimize bias without preference and favoritism. This study is a valuable help for other researchers and practitioners involved in UE and can be used as a guide to quickly choose an alternative from all those present in the literature.

1.5 Discussion and Conclusions

Our research question in this study was whether in the literature exists a common scale/metric for measuring UE. To address this question, this conceptual framework aimed to identify a range of studies that met the criteria and reported engagement measurements to extract conclusions about the methods used. A comprehensive search was conducted to determine as many studies as possible, which included Scopus DB and Google Academics but without excluding proceeding documents, to identify further prominent studies that may not have been

wholly published yet. We only included articles that reported a precise engagement measure.

The number of articles and citations regarding UE studies has been increasing in recent years. As stated before, many disciplinary fields are interested in engagement measurement. Indicatively, in our study, we found that the sector that has carried out the most research on this topic is the Education field which represents 27% of the total documents analyzed; lately, interest has grown regarding student engagement during online lessons. The following field by the number of studies (20%) is health services and their interest in patient engagement during different treatments. Followed by engineering and manufacturing context (19%), this field includes studies related to new technology developments, product design processes, and workers' engagement while developing a specific task. Marketing-related studies represent 15%. Virtual reality applications the 8%. Social services the 4%. Videogames 3%, while other services interested in UE and their perceptions like music, sports or food represent the remaining 4%.

For carrying out the literature review, an initial search was done, then the representative data was selected and filtered according to the scope of the research to create clusters based on data classification. After the review, a total of 1498 documents were analyzed, screened, and selected to understand the methods, tools/instruments, and metrics to measure the UE. We found that many studies described the use of self-report methods, while others used physiological methods.

Based on the results, we classified the methods to measure the UE with a product into clusters. The previous revision is gathered within a framework that organizes the current methodologies as Self-report and Physiological methods. The self-report methods refer to measurement instruments that evaluate engagement from different perspectives. This category included the UE dimensionality (UED) as a way to compare the instruments, allowing a comparison between sub-constructs that defines the interaction level between user and product. It was possible to identify a wide range of dimensionalities considered as the basis of a self-report instrument. However, according to the findings, the multi-dimensionality that better supports the UE analysis includes the emotional, behavioral, and cognitive sub-constructs.

There is a higher prevalence of self-report methods, opening new possibilities for the incursion of physiological methods to identify in real-time physical metrics and establish if a user is more or less engaged. Many of the studies used only self-

report methods to measure UE (despite its reported limitations [15]), and used engagement assessments specific to one context; therefore, generalizability is limited. However, in the last years, there has been an increase in the use of physiological methods.

We explored seven physiological approach methods, finding similarities in the process's measurement phases between the different approaches. These phases allow the comparison of standard data against its variation, usually defined as baseline period, task development period, and in some cases, a resting task period. On the other hand, for some methods (Heart rate, Pupillometry, Posture, Respiratory rate), there is not a numerical scale that classifies whether or not the user is engaged; however, there are insights to facilitate the understanding of the information regarding the UE according to the method used. While for other methods (Skin conductance, EEG, Facial expressions), indices and classification levels define the UE more clearly and concisely. Furthermore, considering these metrics as an additional source of information about the user requirements and desires, it is possible to conclude that the physiological methods still have a wide field to be explored concerning UE. In this context, we consider UE a key indicator in any research field, including interactive design and manufacturing. The interdisciplinarity aimed by UCD methods and the lessons learned from other areas will provide visions that will enhance the current design processes. For that reason, this study described different scenarios, including marketing, health, and education, that can be supportive case studies for future UE applications.

This conceptual framework has analyzed the most significant number of publications available and shows examples of good practices from different fields and domains for both self-report and physiological methods. Additionally provides, whenever possible, the measurement scale and equation used to calculate the UE. Finally, we recognize the challenge of selecting a method for measuring UE since there is a wide range of possibilities between the various existing methods. In this regard, the results of this study can allow future researchers, developers, or designers to consider the UE as one of the most prominent indicators of product/service success and to use this general guideline as support to find the more appropriate method, technique, and metric for measuring the UE based on the requirements of their studies. The results of this investigation have been published and can be consulted at https://doi.org/10.1007/s12008-022-01087-6 [145]

Chapter 2

Design Thinking as a Framework for the Design of a Sustainable Waste Sterilization System: The Case of Piedmont Region, Italy

The benefits of User Engagement have also been explored by deploying iterative methodologies conceived to increase users' involvement along the innovation process. Design thinking (DT), a human-focused design approach, can be adopted to identify challenges and create solutions by focusing on empathizing with end-users. By considering the users' behaviors and needs, DT allows the designing of products and services with which users will be more likely to engage.

In the modern era, developing new methods for the correct disposal of waste is unavoidable for any city that aims to become eco-friendly. Waste management is no exception; treating and disposing of infectious waste should be seen as an opportunity to generate renewable energy, resource efficiency and improve the population's quality of life. Northern Italy currently produces 66,600 tons/year of infectious waste, mostly treated through incineration plants.

This research aims to explore a more sustainable solution. In particular, this chapter presents a conceptual design of the main sterilization chamber for infectious waste treatment. This study demonstrates the possibility of obtaining feasible results based on the analysis of users' behavior through the application of DT. This investigation was carried out under the co-supervision of Professor Stefano Mauro in collaboration with Technologies for Waste Management Company TWM.

2.1 Introduction

Exponential human population growth, rapid industrialization, and urbanization have led to massive waste production [146]. Yet, Brundtland's report "Our Common Future" defined sustainable development as: "the development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [147]. This indicates how, for decades, the international community's concern is outlined in economic aspects as well as environmental and social ones.

In the European Union, Italy has been one country committed to mitigating adverse environmental and social impacts. An example of Italian awareness regarding this challenge is the regulation DPR n.254 07/15/2003. It defines sanitary waste as the waste derived from public and private structures that carry out medical and veterinary activities for prevention, diagnosis, treatment, rehabilitation, and research, and all waste produced by sanitary activities regardless of its nature [148], [149].

Within the sanitary wastes, there is hazardous waste and infectious waste, which refers to waste that could be harmful to humans and the environment [150]. It is crucial to pay attention to the entire process, from the appropriate handling to the treatment and final disposition, and consider that the total elimination of infectious risk can only be achieved using incineration or sterilization.

The typical treatments and disposal systems for handling infectious waste are incineration, sterilization, and subsequent destruction, and in some cases, land disposal [151]. Despite its high cost and effects on the environment, incineration is the most popular method in many contexts [152]–[154]. However, open burning and waste incineration have contributed to a potential risk to human health since, during the incineration process, dioxins and furans (PCDD/Fs) are released [155]. These organic pollutants are considered toxic due to their adverse effects on humans and the environment [156]. On the other hand, traditional steam sterilization facilities usually require two separate phases for the process, one for sterilization and the second to render the wastes unrecognizable [157], leading to increased precautionary measures during the waste transport between the two phases.

In Italy particularly, the report presented by Istituto Superiore per la Protezione e la Ricerca Ambientale (Higher Institute for Environmental Protection and Research) highlights that infectious waste production in Northern Italy is about

66,600 tons/year, equivalent to 46.4% of the national total, of which, the Piedmont region was responsible for the production of approximately 9040 tons/year [158].

The primary method of managing infectious waste in Italy is incineration. Nationwide, approximately 66.7% of infectious waste, equivalent to 95,815 tons/year, was handled at incineration plants; the other 33.3% was treated using sterilization [158], [159]. Additionally, there is the problem concerning the lack of incineration plants for infectious waste or sterilization systems in Piedmont. None of the Italian sterilization plants are located in Piedmont, and there are no incineration facilities in the region authorized by Italian legislation 152/2006 [160] to treat the infectious waste directly [148]. Consequently, all the waste produced is exported outside Piedmont to other regions, which implies moving infectious waste at least 400 km, increasing health and safety risks.

Given the environmental and social concerns that governments and industries are experiencing, the need to develop methods, systems, and processes that allow for correct and effective waste disposal is unavoidable for any city that aims to become smart and eco-friendly. New technologies focused on sustainability and resource efficiency would counteract the negative social impact of this context. In modern days, while experiencing the effects of COVID-19, the treatment and disposal of infectious waste should be seen as an opportunity to explore ways to generate sustainable solutions, use renewable energy, and improve the population's quality of life.

This study aims to develop a conceptual design of the main treatment process in-side a new infectious waste management system in the Piedmont region. To achieve this, we will use the Design Thinking (DT) framework methodology, a validated, human-centered, and iterative problem solving approach that involves stakeholders from various backgrounds [161]. DT has been validated as a methodology that can foster sustainability-oriented innovations [162] by focusing on the users through a flexible development.

This work is part of a larger research project that attempts to build an automatic process (Figure 6) for infectious waste management (EWC 180103), characterized by the use of innovative and sustainable technologies, with the challenge to obtain, as a final result, the recovery and possible reuse of infectious waste as a source of renewable energy. Figure 6 depicts the general scenario of future infectious waste facility management, it should begin with collecting infectious waste directly from

hospitals and other health facilities, then it must be safely and efficiently transported to a storage center for treatment. After verification of the conditions for acceptance (for example, correct handling and proper packaging), the waste should be taken to the main process chamber for sanitization and the complete elimination of infectious risks. In order to execute this operation, the future management system must include a proper vapor and liquid control system. After the sanitization process, the treated material should be discharged to later be transformed using a compression process into a dry, homogeneous, and compact material. The final process of the future infectious waste management system foresees the recovery and possible reuse of this material as potential refuse-derived fuel.

In this study, we focus specifically on the conceptual design of the main process chamber which is responsible for waste treatment and sanitization. Following the waste management system elements proposed by Blackman [157], which include waste segregation, packaging, transport and handling, treatment, and disposal, this study focuses on the treatment technique. We use the conceptual design definition proposed by Pahl et al. [163] as part of the engineering design process, where ideas are concretized into preliminary solutions by identifying the fundamental problems through abstraction and establishing function structures.

The study is structured as follows: first, we explain the methodology adopted and related works. Second, there is the application of each one of the methodology phases, beginning by describing the problem, context, and stakeholders in the empathize phase. Then we proceed to the define and ideate phases for continuing to the prototyping and testing phases. Finally, we report our results and conclusions.

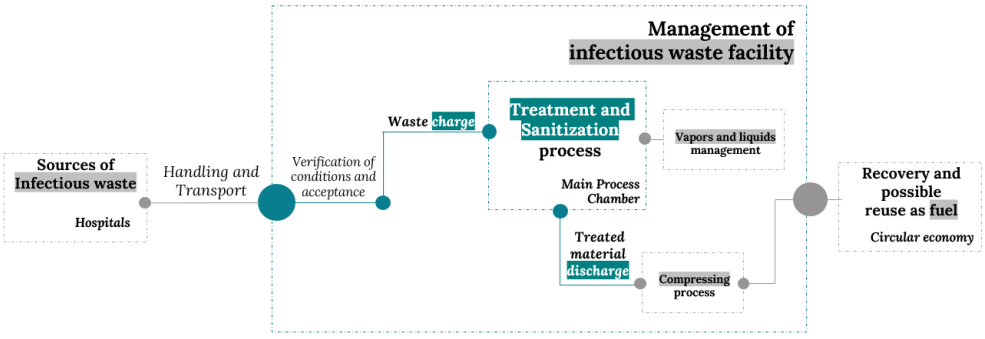


Figure 6: Infectious Waste Management Process

2.2 Methodology and Tools

Recently, Design Thinking methodology has been increasingly used by researchers since it shows a new perspective on the challenges posed by interacting with all stake-holders through multidisciplinary groups, formulating a user-centered solution to these problems. Additionally, DT provides a formal process that captures users' needs [164]. Its approach is based on creativity, simplicity, and technological innovation, making DT an agent of change [165]. Together with other methods and tools, it could create resilient, significant, and sustained interventions [166]. The interest in DT has continued to grow in the last few decades. In recent years, this methodology has been gradually implemented in different companies to create products and services that tend to meet users' needs better, making them an active part of the creation process [167]. DT is presented as a methodology to develop human-centered innovation, offering a lens through which challenges can be observed and the users' needs detected and solved. It is a human-centered innovation process that emphasizes observation, collaboration, rapid learning, idea visualization, rapid concept creation prototyping, and simultaneous business analysis, ultimately influencing innovation and strategy [168].

DT consists of a collection of standard methods in engineering design [169], but unlike other methodologies from innovation management, it involves the activities of both designers and engineers [170]. Features such as problem framing, user focus, visualization, experimentation, and iteration allow DT to be an appropriate method for solving complex problems in engineering, such as creating new (or improved) products, services, processes, or technologies), obtaining environmental and social benefits in addition to economic profits [171]. Through the application of the more than 160 methods and tools associated with DT [172], these design tools help generate and incubate ideas and, therefore, create innovative solutions [173].

From the literature review, we found that DT was selected as a methodology framework for similar applications. One example is the design of an organic waste management system solution to evaluate urban recycling in the city of Depok, involving the community and making use of different methods through the various steps of DT such as SCAMPER (Substitute-Combine-Adapt-Modify-Put to another Uses-Eliminate-Reverse), NGT (Nominal Group Technique), and AHP (Analytic Hierarchy Process). DT was validated as an easy-to-use methodology with a fast implementation time and affordable cost [174]. Another example is the application

of DT for organic waste production and management, specifically in Bengaluru city. In this technical report, researchers implemented the empathize, define, and ideate phases by identifying problems and innovative solutions to improve city waste management [150].

Moreover, DT principles were applied in Ireland to establish a Connected Health Innovation Framework, aligning the healthcare system needs and the software requirements through four stages: identify the healthcare problems/needs, identify the software capabilities, align the users' requirements, and identify the best solution for healthcare management. This study demonstrates how healthcare innovation supported by DT can complement the engineering process, facilitating the understanding of stakeholders in the context of their day-to-day experiences [164].

The process of innovation in engineering is necessary for searching for new ideas that generate value for society, adapting, and anticipating changes. According to the literature review, using DT in the process of defining requirements allows for identifying the stages in which this technique is applicable and how it improves the identification of problems, user and stakeholder needs, collection of new perspectives of solutions, generation of solution options and prototypes that allow the representation these ideas. Moreover, the DT approach helps to establish the appropriate scope of in-novation for sustainability-oriented solutions. Its strong focus on users and stakeholders encourages the development of sustainability innovation that meets the real needs of users. DT focuses on iterative experimentation and ensures positive sustainability effects while reducing the risk of failure and rejection of innovation. In other words, DT is an approach that uses the designer's sensitivity and problem-solving method to meet people's needs in a technologically feasible and commercially viable way.

The previous research provides a foundation that supports the expectations of different investigations about the DT-based approach as an essential but often over-looked asset when addressing sustainability challenges. Lastly, the idea of linking Sustainability Oriented Innovations (SOI) with DT supports how it can help organizations create new technologies, services, and processes intended for environmental and social benefit. SOI challenges like innovation scope, user needs, stakeholder involvement, and sustainability assurance have specific goals within the DT key principles like problem framing, user focus, diversity, visualization, experimentation, and iteration.

The results of the DT approach can also be seen at the social level for this type of industry; it can help users feel part of the development of a typically rejected technology. In this way, DT helps minimize the risk of opposition from the community and phenomena such as Nimby [175].

Therefore, based on the positive results found in the literature and the DT potential for application, we have selected this user-centered methodology as a framework for the conceptual design of the main automatic treatment chamber for infectious waste management in Piedmont.

DT began to be developed theoretically at Stanford University in California (USA) during the 1970s, and its first for-profit application was carried out by the IDEO design consultancy, which then put together a team to create the first d.school in Stanford, being today its principal forerunner and most significant source of experience [176]. Considering the results and the considerable availability of validated case studies, this study has adopted the DT methodology by d.school from Stanford University structured in five phases [177]: Empathize, Define, Ideate, Prototype, and Test. Since the production costs of a functional prototype are very high and are outside this study's parameters, we intend to generate a design prototype according to the definition pro-posed by Polydoras et al. [178], representing our concept with a CAD model. Consequently, for the test phase, we will evaluate the conceptual design.

As Chasanidou [179] states, selecting appropriate methods is essential for correctly executing the DT methodology. The tools can help the team visualize new perspectives and understand the system's complexity. Brown [180] defines three key practices for analyzing a need: insight, observations, and empathy. To get to the insights, we must get as much information as possible about our users and stakeholders during the define phase of the DT methodology. Numerous observation techniques come from anthropology and psychology to empathize in the best possible way and obtain relevant data. Some of them are interviews, context exploration, personas technic, and the Customer Journey Map, used typically during the Define phase. During successive phases, other methods such as brainstorming and focus groups will also be a source of insight, which later will become an input for the definition of the conceptual design requirements.

We considered previously validated studies on DT [181], and after analyzing the benefits of each tool, we selected for every phase of the methodology a set of tools reported in Table 9.

Table 9: DT Methodology phases and Selected Tools

	Objective	Selected Tools
Empathize	Define the context and users, discover their behaviors, ask open-ended questions. Know the user's needs by putting ourselves in the place of the user.	• Context exploration: explore the current scenario, stakeholders, and challenges. • Personas: this technique models users based on their description and provides information about their characteristics.
Define	Based on the insights gained, summarize the problem to be solved. Use an action-oriented approach to express the stakeholders' requirements effectively.	• Customer journey map: this allows us to shape on a chart each of the phases or stages that a user goes through, from when the user has a requirement until he/she uses a service to solve this need. It involves using the user's thinking and feeling to establish ideas for improvement, rephrasing the user's needs as a well-structured problem statement combining the user's needs and the information we have.
Ideate	Generate ideas to solve the problem. Ideas should be shared and reflected upon openly.	• Benchmarking: investigate technics and systems that are currently being used to solve the problem. • Functional decomposition: decompose the concept into more minor problems for analyzing interactions and relationships. • Brainstorming: think of ideas to solve the problem and share the ideas that arise with the other team members.
Prototype	Concretize the idea and compare solutions. Create one or more concepts with which team members can engage.	• Process and Functional interactions: demonstrate an end-to-end solution for a service scenario through the use of sketches. • Computer-Aided Design: create CAD concepts in order to transform preliminary ideas into visual models
Test	Evaluate the concept and collect feedback. If necessary, go back to previous phases until a feasible solution is found.	• Concept scoring: this uses a weighted selection model to evaluate the concepts.

This document describes two groups of people: users and stakeholders. Stakeholders are a group of individuals with a vested interest in the project and are considered key people in the company building a product, often including managers, subject experts, and individuals in charge of verifying compliance with regulations. The user can also be considered a stakeholder; however, not all stakeholders can be considered users. Thus, for this study, the user specifically

describes a person who ultimately uses and interacts with the system and who has an actual behavior in the process. Users will be consulted on their views on their needs and desires and will be considered a data resource for technics such as persona and consumer journey map. Opinions from other stakeholders will be also considered during the study.

2.3 Implementation

The following sections will show the implementation of each one of the DT phases described in Table 9 (empathize, define, ideate, prototype, and test) and the application of the selected tools. To complement the DT definitions, it is important to note that in addition to the five phases reported in Table 9, the DT process can also be described through three stages: inspiration, ideation, and implementation [180]. Inspiration is the initial stage. The first part is understanding the problem, and the second observing how the product is used and how the service is developed. In our scenario, this stage appears during the empathy and define phases. During the ideation stage, it is necessary to generate alternatives and options and to collect ideas to solve the problem by involving users and stakeholders. Notions such as co-creating and brainstorming, typical of the ideate phase, are used in this stage. The implementation stage foresees the prototyping of the possible solution to obtain feedback as soon as possible and, in this way, be able to improve the idea. In our study, the implementation stage corresponds to the prototype and test phases.

2.4 Empathize

During the development of new solutions, user interaction can foster the user's future acceptance of new technologies [182]. In the empathize phase, we began by analyzing and defining the context of our case. We then characterized the potential users and interacted with them using the established empathize tools.

2.4.1 Piedmont Region Context

In 2018, the Italian production of special waste (produced by industries and companies) amounted to 143.5 million tons. The production of special waste is concentrated in northern Italy, with almost 84.9 million tons/year. Between 2017 and 2018, there was an increase in total production, equal to 3.3%, corresponding to approximately 4.6 million tons/year. In particular, infectious-risk wastes produced in Italy amounted to about 144,000 tons/year [158].

From the last data published by the Piano Regionale di Gestione dei Rifiuti Speciali (Regional Management Plan for special waste), we found that the primary producers of infectious waste (Figure 7) are hospitals, with 82% of total production. In second place, subjects who carry out health and assistance activities such as, nursing homes, specialist clinics, research institutes, physiotherapy centers, dental centers, and veterinary services (10.4%). In third place, other health facilities, i.e., outpatient clinics or independent laboratories (5%), and in fourth place, subjects who, while carrying out activities other than "health and assistance" or "veterinary services", have produced infectious waste such as pharmacies and beauty centers (2.6%) [148].

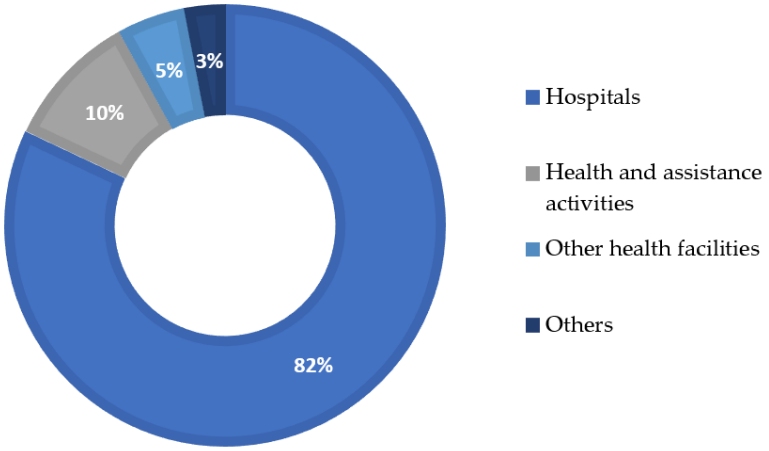


Figure 7: Sources of infectious waste in the Piedmont region, North Italy

In 2018, the Piedmont region produced 9040 tons of infectious waste, but only 3.6% was treated inside Piedmont, in the only incineration facility available and authorized to treat this kind of waste (Figure 8). This incinerator, however, was closed a few years ago. In 2021, all the infectious waste was exported to other regions to be incinerated or sterilized and later destroyed [148], [158].

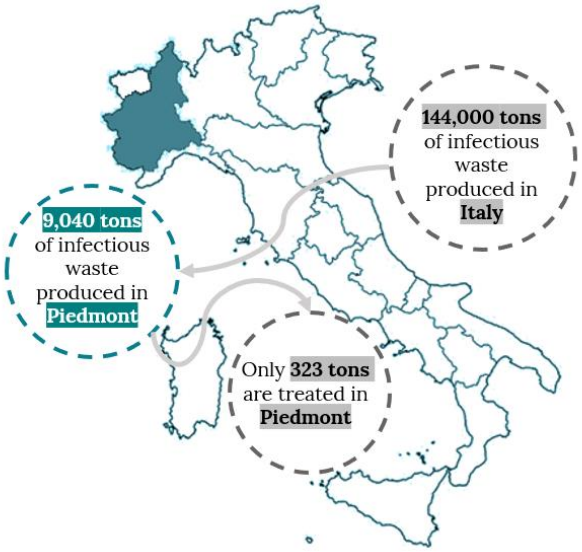


Figure 8: Infectious waste produced and treated in Piedmont in 2018

Consequently, all the infectious waste produced in Piedmont is sent directly or in-directly (after being in a preliminary warehouse) to other regions, mainly Lombardy, Emilia Romagna, and Liguria. According to the Piedmont regional council [183], each waste trip to other regions has a capacity of 5 tons, so it is necessary to make more than 1800 trips in a year to transport all of the infectious waste produced in the region. Additionally, the average round trip distance is 1240 km, creating a high environmental impact, producing yearly 7,886,400 kg of CO^2, 3,360,000 kg of PM10, 7,100,050 kg of NOx, and 4,318,176 kg of CO, indirectly affecting the health of the population and creating environmental damage. Therefore, it's crucial to develop treatment facilities closer to the infectious waste sources within the Piedmont region to mitigate the environmental and health impacts.

2.4.2 Infectious Risk Waste

In Europe, infectious waste is defined and cataloged by the European Waste Catalogue (EWC) as wastes whose collection and disposal are subject to special requirements to prevent infection, and it is classified under the EWC code 180.103 [184].

Infectious waste in Italy is governed by the regulations on medical waste management, decree 254/2003; listed in art. 2, it defines "infectious waste" as not only the waste produced by healthcare facilities but also waste produced outside of

them with similar infectious risk characteristics [149]. In other words, all materials that have come into contact with infected or presumed infected biological fluids are considered infectious waste. Furthermore, the kind of waste that must be collected and disposed of by applying special precautions to avoid infections is identified as HP9 "infectious danger" according to EU regulation 1357/2014. Waste with HP9 characteristics contains viable microorganisms or toxins which are known to be or are considered causes of diseases in humans or other living organisms without concentration limits [158], [185].

In particular, we aim for a system that can treat primarily hospitals and other health facilities' waste, including, according to the characterization of the World Health Organization, primarily: infectious waste suspected to contain pathogens (bacteria, viruses, parasites, or fungi) in sufficient concentration or quantity to cause disease in susceptible hosts, e.g., laboratory cultures, waste from isolation wards, tissues, swabs, materials, or equipment that have been in contact with infected patients; pathological waste, human tissues or fluids, e.g., body parts, blood, and other body fluids; and sharp waste, e.g., needles, scalpels, knives, and blades [186], [187].

2.4.3 Stakeholders and Personas Technic

The identification of stakeholders allows us to recognize users and groups that may be interested or are involved in the study; identifying and grouping them is part of the empathy phase of DT, since users' needs are the basis of our analysis. In our study, we define primary stakeholders as any user who has direct contact with waste, for example, hospital managers, doctors/nurses, patients, waste handlers, carriers, and waste management company workers. There are also external stakeholders, such as government authorities, nearby communities, and research centers.

Using the personas technique, we proceed to characterize our active stakeholders. This tool helps to cultivate an innovative mindset and encourages the team to produce ideas through the representation of the stakeholders [188]. For the creation of personas, we used explorative qualitative interviews. According to Dickinger [189], qualitative interviews have a flexible and continuous design, unlike surveys with rigid structures. The interviewer uses open questions to direct the conversation flow to obtain the most significant amount of information. According to Revella [190], to be aware of the user's patterns, a good rule is to complete at least eight to ten interviews for the personas. In this order, for our study,

we conducted a series of interviews, including three waste management systems managers, two hospitals managers, three workers who are handling the waste, five persons from the nearby community, and ten university students interested in sustainable development, all of them living in Piedmont region. We inquire about their knowledge of infectious waste, waste management systems in Italy, the current Piedmont situation, and techniques. Then we explain our project and ask for opinions.

Depicted in Table 10 there are three of the most representative stakeholders, a worker from the company in charge of waste treatment, a hospital di-rector, and a community member. For each of them, we have reported the gains, pains, jobs to be done, and use cases according to the user profile suggested by Lewrick [181].

From the information gathered through the personas, we identified some of our users' main worries and expectations, mostly related to a safer environment, the safety of operations, regulation compliance, and process innovation. Aligned with DT goals, the community manifests the desire to be included in the development of a new technology and its related process.

Table 10: Personas Technic

	Persona Description	Gains	Pains	Jobs to be done	Use Cases
Franco	Age: 23 years Gender: Male Job: Handling staff at Waste management company. He is a student who works to pay his college fees	Once you have the routine identified, things are easier to do	The work is exhausting, and all the more so because he must get home to study and fulfill more obligations. Sometimes feels afraid of the contagion of diseases due to the handling of infectious waste.	It is essential to use a safe container because there are many risks. It is crucial to consider the storage of the waste, *keep it for the shortest time* while collecting it under optimal conditions. From the beginning, the waste must be packed and sealed correctly. I cannot risk my health.	It should not be just a product but the development of an exemplary process where the *correct handling of waste is done* having minimal contact with people. It is also essential to coordinate with the hospitals to verify the proper sealing of the containers.
	Persona Description	**Gains**	**Pains**	**Jobs to be done**	**Use Cases**

Luisa	Age: 40 years Gender: Female Job: Hospital Director She has a degree in medicine, has been working on health systems management for three years.	Keep the hospital in the right conditions. She wants to continue to be an example in the region and contribute to the country. The priority of a hospital is to save lives; that is why all processes and resources must be focused on meeting this objective.	For Luisa, her team is busy focused on processes to save lives. They do not have much time to apply more methodologies. The approach *must be innovative;* she understands the importance of being sustainable but worries that new methods are costly and not efficient.	Luisa wants a fast and flexible process to be implemented. Does not want to affect process times. The process must be kept for the team and the environment throughout its entire cycle.	Luisa cares about her employees; handling infectious waste must be *secure for the operators.* It is necessary that the process *complies with regulations*. It is a process that can transport and treat infectious waste without taking time from nurses and doctors, who should be doing their main activities.
	Persona Description	**Gains**	**Pains**	**Jobs to be done**	**Use Cases**
Marisa	Age: 78 years Gender: Female Job: Pensionary She is a pensioner and has lived in the neighborhood for 40 years. She likes to read and participate in community meetings in the neighborhood.	It has been a quiet neighborhood. Every project that involves the neighborhood is discussed in the action meeting so that the neighborhood continues to be safe, profitable, and comfortable. We know that waste management is essential.	Marisa cares about the children; she wants them to grow in a *healthy and clean environment.* She is afraid of new treatment plants near their town.	It is important not to generate foul odors, and continuous supervision is needed to ensure no disease. Also, as a community, *we want to be considered* in any decision that may affect us.	It should be a plant with processes well supervised. It must not make noise when it works. The trucks transporting the waste must be within the corresponding hours, comply with biosecurity measures, and not affect neighborhood peace.

2.4.4 Local Regulation

Regarding regulations and their influence as external stakeholders for our study, article 8 of Italian Decree 254/2003 [149] defines the characteristics of infectious

waste treatment. The elimination of infectious risks can only be achieved through incineration or sterilization. Articles 10 and 11 provide specific indications in this regard:

"Infectious waste disposal must be done in incineration plants. Sterilized waste can be used to produce refuse-derived fuel (RDF) or directly to generate energy. Sterilized waste can be disposed of in incineration plants for solid waste or (if these alter-natives are not available) they can be disposed of in landfills for non-hazardous waste, for a limited period".

From this information, we identify the use of sterilization as a potential design strategy and the opportunity to analyze the RDF production for a future scenario.

2.5 Define

Based on the insights gained from the empathize phase, we use the consumer journey map (Table 11) to bring together the context of our research, the activity stages, and the expectations and worries of our stakeholders. It is divided into macro phases, beginning when the wastes are collected from the healthcare unit and ending with the final process in the treatment facility. The visual approach of this tool allows for understanding the overall picture of processes and users' needs. As Lemon and Verhoef [191] indicated, it helps to provide a deep understanding of the user experience and can act as the basis for innovation, improving that experience.

Summarizing the problem in Piedmont, there are challenges relating to the absence of incineration plants for infectious waste. The lack of sterilization systems aggravates this issue. Furthermore, the authorized incineration plants are not adjacent to Piedmont, which leads to the need to make long journeys for quite significant distances, even to the order of 400 km.

From the users' point of view, there is concern about the potential risk of new in-cinerator plants, the safety of operations, compliance with regulations, and the distances traveled to carry the waste. Furthermore, they expressed their satisfaction at being included in the ongoing investigation. They communicated their interest in being in-formed about what would happen to the final material after the treatment.

Table 11: Consumer Journey Map

Stages	**Transportation outside Piedmont**		**Handling**		**Main Process**	**Handling**	**Transportation to final disposition**
Activities	Recollection of waste containers from the hospital	Transport of containers to facilities outside Piedmont	Carrying the containers inside the factory to the main chamber	Load the waste into the chamber for treatment (normally incinerator)	Chamber closing and beginning of the process	Unload the resulting material	Transport of resulting material to final disposition
Thinking and feeling	The operator is concerned about the waste storage in the hospital for a long time. Hospital managers expect a secure procedure that complies with regulations.	Nearby community is worried about the long-distance transportation of infectious waste	The operator must perform many journeys inside the facility carrying out the containers, but he is used to it.	The operator is afraid of getting in contact with an infectious risk	The most commonly used method is incineration (outside Piedmont); it produces risks for health and the environment.	The operator works in an "automatic" way, every day, the same steps.	The nearby community is concerned about the final disposition of the resulting material
Ideas for improvement	Develop a standard process capable of collect waste in the shortest possible time	Develop an innovative and closer treatment facility	Automatize the operation; the operator should only verify the proper sealing of containers	Automatize the operation	Consider other methods different from incineration	Automatize the operation	Consider the possibility of using treated waste as a potential RDF

Once we identified the users' main concerns (or insights), we expressed the users' needs as a requirement, considering the users' thinking and feeling information and the ideas for improvement obtained from the Consumer Journey Map. In Table 12, we establish the requirements for the conceptual design of the main treatment process.

Table 12: Conceptual design requirements

User Need	Requirement
The user expects a safe and fast procedure.	• Develop a standard process capable of treating waste in the shortest possible time.
A procedure compliant with regulations.	• Develop a procedure compliant with regional regulations.

Shorter-distance journeys while transporting waste.	• Develop an innovative and closer treatment facility inside Piedmont.
Inside the facility, the user wants a secure operation with less handling.	• Automatize the operation to guarantee minimum contact and handling.
Users expect an innovative solution different from the current one (incineration).	• Consider other methods different from incineration.
The user wants to know what happens after the treatment.	• Consider the future possibility of using treated waste as potential RDF.
The user wants to be included.	• Use user-centered design approaches to include users.

2.6 Ideate

The requirements determine the function representing the intended relationship between the inputs and outputs of a system or machine. The goal of the conceptual design ideate phase is to explore the concepts that may address customer needs. It includes a combination of external search employing benchmarking analysis, internal problem solving through brainstorming, and the exploration of solutions. As Pahl et al. [163] indicate, we need a system with a clear and straightforward reproduced relationship between inputs and outputs to solve a technical issue.

To identify the initial relationships from the preliminary requirements established in the define phase, we began by analyzing the requirements related to consider other methods different from incineration and procedures compliant with region regulations.

Italian regulations allow two types of treatment management for infectious waste: incineration or sterilization. Since we want to explore other methods different from incineration, we refer to the active regulation of infectious waste management. Concerning sterilization, the Italian Environment, Government, and Land Protection Department defines it as a physical (heat, ionizing radiation, microwaves) or chemical treatment that allows for a reduction of the microbial load to guarantee an S.A.L. (Sterility Assurance Level) not less than 10^{-6}, which is a 1 in 1,000,000 chance of a non-sterile unit. Sterilization must be carried out according to the UNI 10384/94 Standards employing a procedure that includes shredding and drying for non-recognition and greater effectiveness of the treatment and waste volume and weight reduction [149].

2.6.1 Standard UNI 10384/94

Within the standards regarding waste management, there is the ISO 14001, which describes a formal approach to handling waste, the CEN/TS 17159 that guides the management and safety of high-risk materials and waste, and in Italy, particularly the UNI 10384 [192].

The UNI 10384 standard: "Systems and processes for the sterilization of hospital waste," which dates back to 1994, and is managed by the Ente Nazionale Italiano di Unificazione UNI (Italian national unification organization), provides the criteria for the design, operation, and verification of sterilization systems for infectious waste from public and private healthcare facilities. Furthermore, for treatment systems that involve thermal destruction and systems that use ionizing radiation.

Regarding the concept design requirements, the UNI 10384/94 specifies that:

- All the necessary precautions must be taken so that the loading operations in the sterilization system take place in safe conditions for the operators and the environment.
- The sterilization cycle must be carried out automatically through a succession of phases.
- The sterilization conditions, within established limits, must be uniformly achieved in the sterilization chamber, kept at the critical point for the pre-established time, and reproducible.
- The sterilization chamber must be equipped with suitable closure or confinement systems. The sterilization cycle must not start until the closing system is closed, blocked, and, where necessary, sealed.
- If a loading device is used, the waste must be cased without interference between the containment systems and the loading door.
- The chamber must be equipped, in addition to the standard operating equipment, with those necessary for carrying out sample tests to detect the appropriate level of sterilization.
- The materials used to build the chamber must resist chemical and physical aggression from the process and treatable waste.
- The number and position of sensors inside the chamber must be specified.

2.6.2 Functional Decomposition

The next step for establishing the relationships in our conceptual design is decomposing the problem functionally, representing it as a single black box operating on material, energy, and signals, as suggested by Ulrich et al. [193]. The next stage will divide the single black box into sub-functions to obtain a more detailed description of every element and their task-oriented to achieve the entire system goal.

After selecting sterilization as a treatment method, considering the requirements and restrictions of regulations, we represented the first black box of our sterilization chamber in Figure 9.

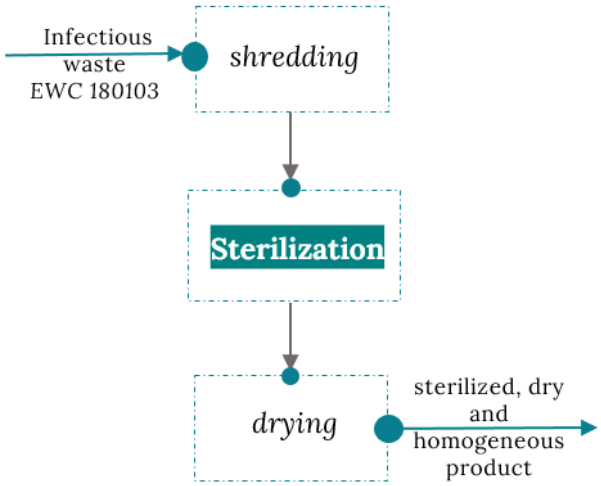


Figure 9: Early black box for the sterilization chamber

2.6.3 Treatment Methods Benchmark

In concept generation and as part of the DT ideate phase, it is beneficial to investigate current treatment methods used to solve the problem. Ulrich et al. [193] define benchmarking as exploring existing processes with functionality similar to the system under study. In our case, benchmarking can reveal current concepts that have been implemented and information on the strengths and weaknesses of treatment methods. In this regard, we analyzed currently used sterilization methods and then investigated relevant concepts in Italy for infectious waste treatment, different from incineration.

- Sterilization Methods

  Xiao and Hancock, and Lambert [194], [195] define some of the most used methods for the disposal of infectious waste:

a. Microwave sterilization: The method refers to the inactivation of infectious bacteria by the heat generated from the microwave vibration of the water molecules, achieving the disinfection of the objects. It is suitable for processing infectious and pathological waste (except human organs and infectious animal carcasses); it is not ideal for the treatment of pharmaceutical waste or chemical waste. In economic terms, it is not feasible due to high construction and operating costs.

b. Chemical disinfection: This method allows for the disinfection of waste with chemicals that eliminate bacteria and viruses. It uses dry and wet compounds that require the same treatment, and waste must be crushed and disinfected. The disadvantages of using wet chemicals are residual liquid, which can be an environmental pollutant and not suitable for all healthcare waste.

c. Pyrolysis: Pyrolysis is a thermochemical reaction technology. Suitable for all types of medical waste, but due to operation and maintenance requirements, this method is the most expensive. Furthermore, it is not easy to achieve stable combustion, producing exhaust gases and waste that can generate a secondary source of pollution.

d. Steam sterilization: This method applies high temperatures to generate steam that kills microorganisms and disinfects waste. The advantages of this technology are low installation and maintenance costs; it does not affect the environment and can be applied to all infectious waste.

Since we aim for a system that can also treat pathological waste (including human anatomical residues), microwave sterilization is not feasible. At the same time, chemical disinfection and pyrolysis can generate residual material (liquid and exhaust gases, respectively), which can be a pollutant by themselves. On the other hand, steam sterilization seems a feasible and secure treatment method suitable for our research.

According to Health Care Without Harm (HCWH) [196], in the European Union, some of the best practices for infectious waste that use non-incineration technologies range from small units for use at or near the point of generation to high-capacity systems for large medical centers. Most non-incineration

technologies used in the EU employ low-heat thermal and chemical processes. Low-heat thermal processes use thermal energy to decontaminate the waste at temperatures insufficient to cause a chemical breakdown or to support pyrolysis or combustion. In comparison, chemical processes employ disinfectants such as dissolved chlorine dioxide, sodium hypochlorite, peracetic acid, or dry inorganic chemicals. Some of these technologies include autoclaves in the Netherlands, steaming and drying in France, chemical treatment in Spain, steaming and compaction in Germany, as well as vacuum-steam and steam-fragmentation. Microwave treatment in Austria and other countries such as Italy, France, Germany, Slovenia, Serbia, Slovakia, and Romania. Chemical processes are also used in Italy. Finally, electron beam technologies in Belgium and other countries.

Additionally, in the study "Assessment of Medical Waste Disposal Technologies Based on the AHP"[197], a hierarchical structure model is used to analyze and evaluate five types of disposal technologies quantitatively for infectious waste in China. The classification weights of the optimal and suboptimal alternatives were studied using sensitivity analysis. The results show that the comprehensive benefits of high-temperature steam sterilization in infectious waste treatments are the best com-pared to the other methods in terms of social, environmental, technological, and eco-nomic factors. These overall results allowed us to define steam sterilization as the selected treatment for the main chamber.

2.6.4 Italian Concepts Initiatives

Next, we considered some relevant infectious waste sterilization initiatives in Italy. We looked for systems (including Italian patents) that have a well-established process. In Italy, we found three companies that include within their services the use of sterilization methods. However, we did not find evidence of the use or field implementation of these systems. The processes used are explained in Table 13, according to the public information reported by the companies.

Table 13: Italian Initiatives

System	Process
A [198]	Waste is pre-treated by grinding and conveying through sealed stainless-steel screw conveyors, followed by grinding through shaft shredders, and finally, refining the sterilized product utilizing the moist heat sterilization process.
B [199]	The shredding phase starts with a four-shaft shredder. The shredding of the material takes a variable time, depending on its consistency. The shredded material is collected

	in a storage chamber, then transferred in containers to the sterilization chamber; the heating process occurs by injecting hot air into the chamber.
C [200]	The process consists of a combination of dry heat sterilization and microwave. Then the waste is transported to an external facility for the grinding process.

From the different available techniques of sterilization and considering the initiatives reported in Table 13, we can conclude that most of the systems differ from each other by the sterilization method, the shredding technology, the way of heating the chamber, and the transportation from the shredding machine to the sterilization chamber.

2.6.5 Brainstorm for Ideation

Convergence is crucial in collaborative problem-solving and decision-making, as the team must focus its resources on the most promising ideas [201].

Brainstorming allows the team to think of ideas to solve the problem and share the thoughts that arise. After analyzing different possibilities for the main chamber, we used the brainstorming technique to converge into preliminary ideas. Figure 10 shows the most discussed methods in the technical brainstorming sessions. For each function, the solution selected is underlined. The selection was made considering the feasibility of construction and operation in Italy, success stories, cost, and originality for the Piedmont region.

We decided to use moist heat sterilization for the sterilization method because of its nontoxic characteristics, cycle time, cost, and safe operation [202]. We have also noted that the systems analyzed in Table 13 always transport infectious waste from the sterilization chamber to the shredder or vice versa, incurring more space, logistics, and risks. For that reason, we concluded that a suitable alternative could be the design of a single camera for sterilization and shredding, which will be explained in the next DT phase. Regarding the mechanism for heating and drying, we selected electrical resistance heating because of its efficiency and simplicity by converting nearly 100% of the energy in the electricity to heat. The shredding process will be carried out through rotating blades and counter blades at the bottom of the sterilization chamber. Finally, we decided to explore two options for waste loading, one using a conveyor and the second using an elevator. For the material unloading, we will use a gate at the bottom of the chamber to take advantage of the blades and the force of gravity. All the concepts will be further elaborated on and explained in the next section.

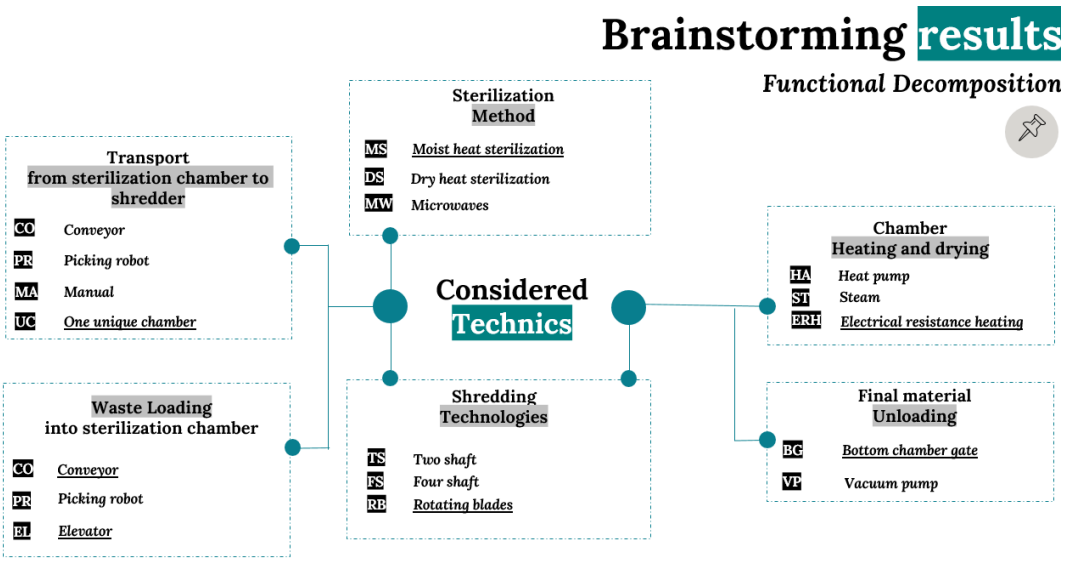


Figure 10: Brainstorming and functional decomposition results

2.7 Prototype: A Conceptual Design

The prototype phase in DT aims to concretize the idea by creating an approximation of the product, reflecting on its features and eventual improvements. Ulrich et al. [193] define the prototype as an approximation of the product along one or more dimensions of interest. Any entity presenting at least one aspect of the product of interest can be viewed as a prototype. Virtual prototypes can be represented using drawings, mathematical models, simulations, and CAD models.

In our study, we intend to create a design prototype according to the definition given by Polydoras et al. [178]. Prototypes can be classified according to their ability to serve the distinct stages of the design process; a design prototype mostly represents the form and functional relations of the product. A design prototype allows designers to evaluate various aspects of their ideas before committing to the expense and risks of producing a commercial quantity [178], [203].

With this aim, according to the previous phases' results, we focused on the conceptual design. To achieve this goal, we defined the process, its functional interactions, and the sterilization cycle and then proposed two CAD concepts.

2.7.1 Process and Functional Interactions

The treatment system aims to transform infectious waste into a dry and homogeneous product with no recognizable parts, which is stable over time. The

final product could be stored for long periods before its disposal and recovery. The designed process aims to obtain a fine shredding of the waste, the pulverization of glass parts, and the total elimination of liquids, contributing to the reduction of weight and volume. This system is based on the moist heat sterilization method. It works under the same conditions as steam autoclaves. The combination of time, temperature, and humidity are achieved in a closed environment under vacuum conditions. However, this process's peculiarity consists in treating the waste to a temperature up to 151°C with the presence of humidity and liquid water, operating under vacuum conditions, without diffused pressure as in autoclaves.

The system (Figure 11) consists of a closed cabin (a) with all the devices inside it, the sterilization chamber (b) automatically performs thermal cycles that include shredding and evaporation of liquids, overheating up to 151°C, sterilization at 151°C, through continuous dosing of water transformed into steam because of the operative conditions, and for an adequate time to ensure microbial elimination. The process ends with a cooling phase and the discharge/unloading of the dehydrated final material.

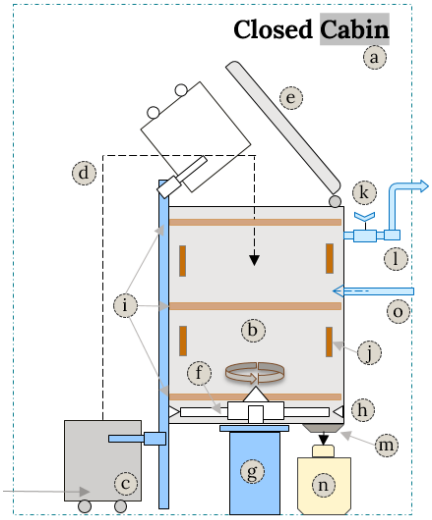


Figure 11: Sterilization chamber: conceptual functional interactions

The waste is introduced to the system using apposite containers (c). An automatic loader (d) deposits the waste inside the sterilization chamber (b) after the lid (e) has been automatically opened. The sterilization chamber (b) structure is a vertical cylinder in AISI 306 stainless steel, equipped with a sealed lid (e) made in high-temperature resistant silicone rubber gasket and hydraulic locking systems. All the phases of the sterilization treatment, including loading and unloading, occur automatically inside the cabin (a) without moving the waste outside the chamber until the process end.

In the lower part of the chamber, there is a two-blade Hardox 500 stainless steel rotor (f) driven by an electric motor (g). The blades act like hammers; stationary blades (h) are mounted in correspondence inside the chamber to ensure the necessary contact and, therefore, the material crushing. This friction produces an additional source of heat, valuable for our operation. In the high, middle, and lower sections and around the perimeter, there are electrical resistances (i) that heat further the chamber (b) in a controlled way. Across the entire chamber height (b), there are ten thermocouples (j) installed for measuring the material temperature, six at the bottom chamber along the perimeter and four more at the middle and upper section.

The chamber is connected to a throttle valve (k) for vacuum control and then to a vacuum pump (l). At the end of the treatment, the unloading gate (m) automatically opens, and the product is discharged by centrifugal force into apposite bags (n). The system is kept in slight depression during the entire treatment cycle using a throttle valve (k) and the vacuum pump (l). Considering the variable composition of the incoming waste in terms of typology and, therefore, in terms of intrinsic moisture, the system includes a valve (o) for pouring the necessary water into the chamber to reach and guarantee the sterilization conditions.

After the waste is loaded, the chamber lid closes automatically, and the rotor at the bottom starts spinning at a low speed. The waste is shredded while the rotor speed progressively increases up to about 1000 rpm. The mass heats up, thanks to the thermal energy generated by the rotation and friction of the blades. This operation leads to the release of intrinsic moisture from the waste. In this way, the temperature gradually increases until it reaches the value of 151°C. Extra water can be added in this phase if the intrinsic moisture of the waste would not be sufficient to reach the required sterilization conditions. Compared to the traditional moist heat sterilization process used in autoclaves, this process does not operate with saturated steam but with unsaturated steam on a finely shredded material, operating at higher temperatures but with significantly lower pressures.

2.7.2 Sterilization Cycle

According to the previous description, the sterilization cycle follows a sequence of seven steps:

1. Waste loading: The waste is loaded into the sterilization chamber using an automatic loader, then the lid is automatically closed at the end of loading.

2. Shredding and Heating: After closing the lid, the rotor begins to rotate until the material is pulverized and the temperature reaches 100°C. The blade's profile should be designed to create turbulence at the bottom of the chamber, facilitating the mixing and avoiding depositions on the walls.
3. Evaporation and overheating: The heat generated by the friction of the material should cause the vaporization of the humidity contained in the waste, and the temperature should remain stable at 100°C. Humidity and temperature are constantly measured using a probe designed for test chambers at high temperatures.
4. Overheating: Once all moisture has been removed, the generated heat raises the temperature of the material to 151°C. Extra water can be added if the waste's intrinsic moisture is not enough to reach the sterilization conditions.
5. Sterilization: The material temperature is maintained at 151°C through water dosage and controlled by the thermocouples. When coming into contact with the material, the water evaporates and becomes steam. The water dosage is controlled so that the heat absorbed by the water evaporation balances the heat produced by the material friction. Additionally, there is extra heat coming from the chamber walls using the electrical resistances. This allows for keeping the material moist at a high temperature. The whole chamber must be kept at 151°C for at least 3 min during each operating cycle to ensure the correct functioning of the sterilization system.
6. Cooling and drying: The rotor speed decreases, and consequently, so does the heat generation. If needed, water is sprayed, lowering the temperature to 100°C. Then, through a vacuum pump, the temperature drops adiabatically until room temperature is reached. During this phase, the heat absorbed by water evaporation exceeds the heat generated by the rotor; therefore, the temperature drops.
7. Unloading: The treated material is discharged by centrifugal force through the discharge gate located at the bottom chamber. Once the material has been completely discharged, the rotor stops.

2.7.3 Computer-Aided Design (CAD)

During the DT prototype phase, CAD provides a visual manifestation of concepts and supports the generated ideas' transformation into feasible and testable models [161]. CAD concepts can be quickly created and experienced. It can support team communication by facilitating conversations and feedback regarding solutions for a particular product [179].

According to the process and functional interactions, we propose a virtual prototype, represented by two concepts using CAD. Due to the importance of the internal process of the chamber, it remains invariable for both concepts. The main differences between them are related to the uploading transportation system.

- Concept 1: Automatic Elevator Model

The first proposed concept (Figure 12) consists of a stainless steel trolley to carry all the waste and an automatic uploading system that raises and overturns the loading trolley, allowing the material deposition directly inside the chamber.

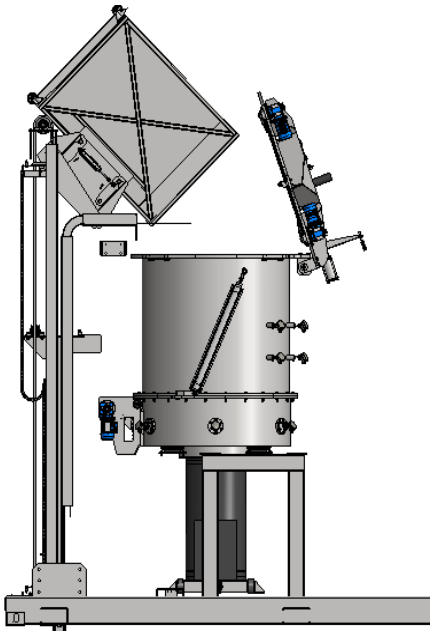


Figure 12: Automatic Elevator Model

- Concept 2: Conveyor Belt Model

The second concept (Figure 13) consists of a conveyor belt system for loading waste containers. The conveyor system transports the containers automatically up to the open lid. Then, from a closer distance to the lid, the containers automatically open one by one, depositing the waste inside the chamber.

For both concepts, the operations inside the sterilization chamber are the same as reported in the process and functional interaction section.

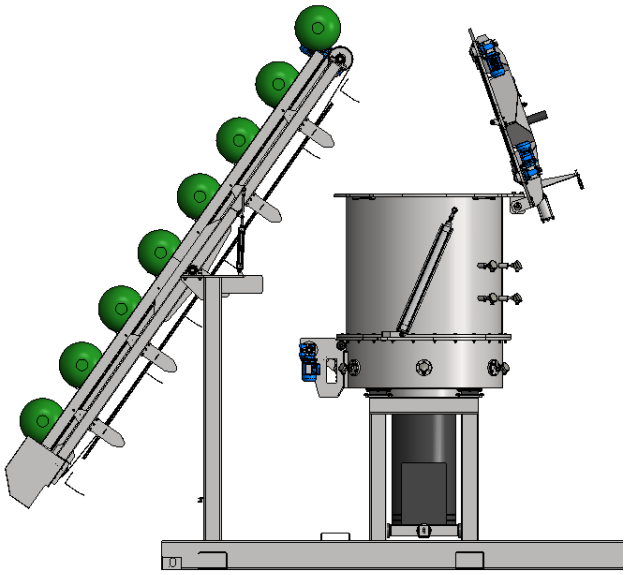


Figure 13: Conveyor Belt Model

2.8 Test: Concept Evaluation

The fifth and final phase of DT corresponds to the test. According to Bresciani [204], visual representations can guide the designer's work within a design framework. They allow for bringing together academic knowledge and the practice of design, providing a visual reference for users and stakeholders, in this way, they can support the design process.

This section evaluates the virtual prototype (represented by concept models 1 and 2) according to the user's requirements, then collects feedback for further improvements. The test phase results were obtained during focus group meetings that included the development team, experts, users, and other stakeholders. For the test phase, we have used the concepts designed in the previous section, represented by their CAD models (Figure 12 and Figure 13).

We use the concept scoring technic (Table 14) proposed by Ulrich et al. [193] to evaluate the concepts. It uses a weighted selection model to evaluate the concepts variants against the requirements and other criteria deemed relevant by the team. The selection criteria were determined according to the user's expectations and the Italian regulations described in the previous phases. For every criterion, the team analyzed and agreed on the weight assigned, considering that in this phase, we are performing a feasibility analysis for a conceptual design. The same consideration

was used for rating the concepts. They were evaluated on a scale of 1 to 5, five being the best and one the worst.

Table 14: Concept Scoring

		Concept 1: Elevator		Concept 2: Conveyor Belt	
Selection Criteria	**Weight**	**Rating**	**Weighted Score**	**Rating**	**Weighted Score**
Standard process.	5%	4	0.2	4	0.2
Safe for the environment.	5%	4	0.2	2	0.1
Includes shredding and drying.	10%	5	0.5	5	0.5
Safe operations with minimum handling from workers.	10%	4	0.4	1	0.1
Sterilization cycle carried out automatically according to a succession of phases.	10%	5	0.5	5	0.5
The sterilization conditions are kept at the critical point for the pre-established time and are reproducible.	15%	5	0.75	5	0.75
Loading operations are safe for operators and the environment.	10%	4	0.4	3	0.3
Suitable confinement system. The sterilization cycle must start only after the lid is closed.	10%	4	0.4	4	0.4
The loading device allows the waste to be cased without interference between the containment system and the loading door.	10%	4	0.4	2	0.2
Materials resistant to chemical and physical aggressions.	5%	5	0.25	5	0.25
	Total Score		4.0		3.3
	Rank		1		2
	Continue?		Develop		No

Both concepts used a method different from incineration and were designed to include the users' perspectives. At the beginning of our exploration, stakeholders specified these requirements; both systems are consistent with them, so these parameters are not included in the evaluation.

It is possible to determine the concept ranking using a weighted sum of ratings. After analyzing both concepts, the results show that concept 1 is more promising than concept 2, with a score of 4.0 against 3.3.

Concept 2 has some downsides due to the loading system that could generate unwanted losses in the environment when opening each compartment to deposit the

waste inside the chamber. Additionally, concept 2 requires more handling by the operators as they have to locate different compartments on the conveyor. The same happens during cleaning, which should be done one container at a time. On the other hand, concept 1 has a single active trolley, controlled, and transported by the elevator, that later deposits all the waste material inside the chamber, all in a single step, allowing for faster loading times with fewer risks. In this context, we decided to go ahead with concept 1.

After the concept scoring analysis, however, new suggestions for improvement were proposed. The first is the need to add an extractor hood that absorbs any unwanted material escaping from above the chamber. The second is related to vapor and liquid management during the shredding and sterilization process; all the water due to humidity is evaporated. The vapor leaves the chamber through a duct and is then extracted by the vacuum pump. After that, we will include a scrubber for the condensation of water vapor, the absorption of entrained vapors, and dust removal. Finally, regulations request that we have a system for carrying out quick tests.

2.9 Results

After performing the five phases of DT, we got a final and preliminary concept of the main treatment chamber for an infectious waste management system in Piedmont, Italy. This conceptual design responds to the users' expectations and complies with regulations. When the test phase concluded, some relevant suggestions emerged, leading to the final conceptual design of this study (Figure 14 and Figure 15). It includes an extractor hood to eliminate any possibility of unwanted material dispersion inside the closed chamber and a sampling device for carrying out the test and sampling extraction under contained conditions. For future steps in the general project design, it is planned to add a scrubber for pollutant control and removal. Our concept design is, therefore, delimitated until the phase before the management of liquids and vapors.

Figure 14a shows the entire automatic chamber system with the extractor hood. Figure 14b shows the rearview and allows us to visualize the space where the trolley will enter to discharge the waste material into the chamber.

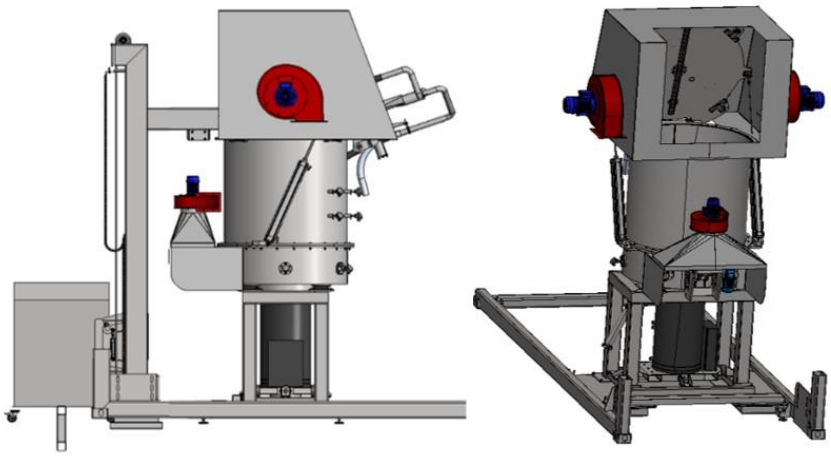


Figure 14: Automatic Chamber System. (a) Extractor hood (b) Rear view

A section view of the chamber is represented in Figure 15a; the rotor blades are in the lower part, along with the counter blades. It is possible to visualize two of the ten thermocouples and the automatic lid. Figure 15b shows the safety extraction valve for the sampling withdrawal test located at the bottom of the sterilization chamber. This valve will allow for the extraction of a sample of the final material after the treatment to evaluate its efficacy.

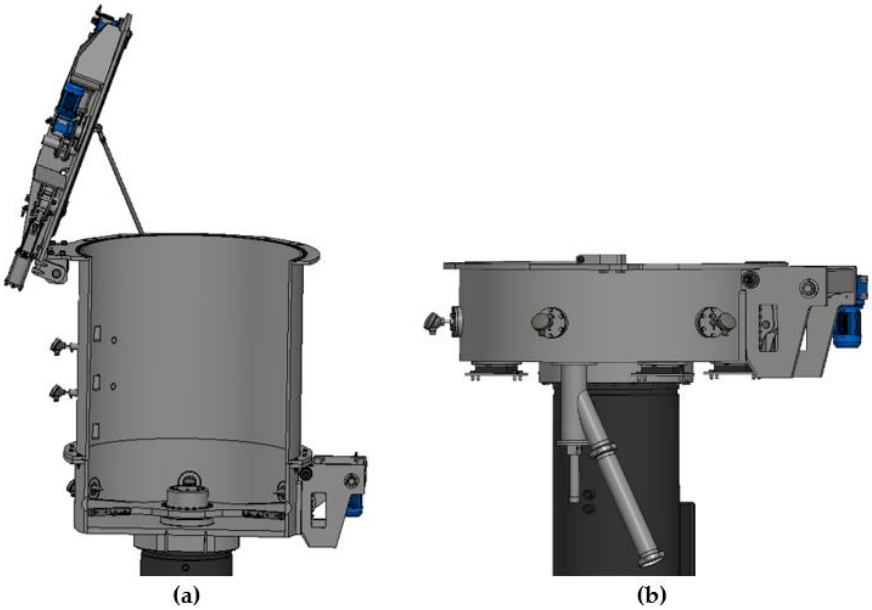


Figure 15: Automatic Chamber System. Chamber section view (b) Sampling extraction valve

DT seeks to define solutions where three aspects converge: desirability for the end-user, feasibility, and financial viability. DT brings together what is desirable from the point of view of the users and stakeholders with what is technologically feasible and economically viable [180]. To validate the desirability, we spoke with stakeholders and potential users during the empathize phase to understand their concerns and de-sires; we have summarized these thoughts, commonly referred to as "pains and gains" in Table 10. In turn, the feasibility involved designing (during the prototype stage) two virtual prototypes of the solution, evaluated later by experts, stakeholders, and users during the test phase. Creating a virtual design prototype enhances financial viability since the production costs of a functional prototype are very high. In this way, creating a conceptual design minimizes the economic risk by being able to improve the design without incurring the costs that would entail modifying a physical prototype.

This section concludes the conceptual design of the main sterilization chamber. For future studies, the idea of including handling robots to perform the trolley loading operations could be further analyzed; this would eliminate the workers' handling completely, and this way, they would be in charge only of activating the automatic cycle and operations control.

Finally, another potential future study regards the use of treated waste, since according to Italian regulation [149], the sterilized infectious waste can be used as a means of producing energy adopting the EWC 191210.

2.10 Discussion and Conclusions

High levels of UE are typically associated with a positive user experience, and can be achieved through a variety of factors, such as ease of use, relevance to the user's needs, and the overall aesthetic appeal of the product or service. Likewise, innovation and new technologies development are essential for most cities that aim to foster an ecofriendly environment. Potential smart cities request more recent systems in shorter time intervals, often customized to their own needs. Companies and research centers must collaborate closely within their organization and with partners located in various parts of the world to meet these needs. At the same time, companies have to manage increasing technology and manufacturing complexities due to a quickly growing number of environmental and regulatory rules and requirements. Using collaborative tools and strategies, such as DT, for managing product data and integrating and automating business processes generally results in efficiency improvements. In particular, the knowledge in this domain can be applied

to the context of eco-sustainable equipment and strategies, working together with users and stakeholders.

UE is a crucial component of the DT process, as it helps designers to validate their ideas and assumptions, gather feedback, and make iterative improvements to their designs. Through a combination of user research, prototyping, and testing, designers can ensure that their solutions are well-aligned with the user's needs and preferences. This project therefore, explored the application of the DT methodology in engineering and sustainability. Its application in technical areas allowed us to explore the methodology and apply it concretely. The DT approach as methodology allowed the team to work under an established framework, following a series of phases and tools. DT guided the conceptual design, beginning from a general idea to finally being able to produce a CAD prototype. The first phases (empathize and define) allowed us to understand the stakeholder's perspective and context and include their suggestions in the development of the study. The personas technique and Customer Journey Map engaged not only with the users but also with the team members, gathering the stakeholder's points of view effectively.

The ideate phase was essential to transform these ideas into visual models. The functional decomposition acted as a conductor to understand and solve, step-by-step, each subproblem of the entire system, understanding their interactions and relations. The brainstorming helped the team to converge on solutions considering all the opinions.

The prototype phase, including brainstorming and CAD tools, concretized the idea into a conceptual design represented by two virtual concepts. Following the DT directions, these concepts were designed based on the users' needs and the current Piedmont region regulations. Users expected a safe and standard process capable of treating waste quickly, a procedure compliant with regulations different from incineration, minimum handling, and shorter distances journeys while transporting waste.

In this way, the study problem is framed and oriented according to the requirements. Many other concepts could be generated using this DT framework. Still, we decided to focalize our efforts on creating a feasible concept, especially in the design of the sterilization chamber. Due to the cruciality of this operation inside the system, we prefer to be cautious in selecting the technique resulting from the brainstorming session.

In the last DT phase, we analyzed and compared the two concepts using the concept scoring method. We established selection criteria according to the stakeholders' requirements, users, and regulations on this matter. We then assigned the weights for each criterion and concept according to the team's expertise; it does not mean that the weights are ideal or unique, but that they are certainly a reasonable approximation in-side a feasible exploration of concepts. Concluding the test phase, we asked experts for feedback to improve the final concept.

The feedback gave us suggestions on how to improve the concept and insights for the future steps of the project. Our concept "delimits" with the vapor and liquids management system; therefore, for subsequent studies, we propose a scrubber to perform the operations of pollutant control. Also, there is evidence of the potential use of the treated material as RDF. In this regard, for future steps, it could be interesting to con-sider a pelletizer after sterilization for compressing and molding the final material for later storage. In this way, the current paradigm that uses incineration as the primary treatment process within a linear economy approach will change to a new scenario, using sterilization and a compression process to generate RDF that could be re-integrated into the production cycle within a circular economy approach.

Compared with other existing facilities, the main improvements of this design are at a local level, the increase in the production and development of own technologies for managing infectious waste, and looking for new treatment and energy recovery processes. Specifically, in Italy, one of the main improvements compared with existing facilities is the use and management of technologies different from the current waste incineration paradigm. Then, an industrial process that guarantees perfect sterilization of the treated waste to obtain a product intended for energy enhancement through a new completely automatic and locked process for the treatment of infectious waste through shredding and sterilization. The whole process takes place automatically and is isolated inside the main chamber, minimizing the risks for the workers. In addition, it is expected to treat the sterilized waste further to generate de-rived fuel and enhance the final product. Moreover, this process operates with un-saturated steam on a finely shredded material, operating at higher temperatures but with significantly lower pressures.

Finally, this investigation is a positive example of how to apply the DT methodology as a framework for new technological designs. With the application of the DT during the development of this study, it was possible to analyze the process holistically, considering the perspectives of the technological and social

environment and the opinions of experts from the industrial sector, users, and stakeholders, in order to develop a technologically-based conceptual design, obtaining satisfactory results for the parties interested in this project.

One key aspect of the DT is a focus on UE. This means that designers and developers strive to understand the user's perspective, needs, and goals in order to create solutions that are relevant, useful, and enjoyable for the user. At a social level, the approach of the DT method helped users engage with the development of a technology that usually is rejected. This study provides a successful case of the application of DT in a sector where few studies have been carried out, leading to an increase in interest and opening possibilities for future research. Additionally, it provides a demonstration of applied tools for future research that intend to use DT for similar processes.

DT can be a powerful tool for enhancing UE and creating positive user experiences. Through this research, we found improvement opportunities for infectious waste management in the Piedmont region in Italy. To contribute to this challenge, DT included the users' needs and involved the community, an essential aspect of sustainable development for eco-friendly cities. The concept result of this study is framed within a feasibility analysis; therefore, it is not definitive. As part of the project, a functional preproduction version of the chamber must be manufactured to verify its performance. This study supports the continuation of the subsequent development phases of the entire system represented in Figure 6. We expect that this study could be used as a reference for future investigations related to the application of Design Thinking in engineering designs oriented to sustainability, resource efficiency, and waste management.

The results of this investigation have been published and can be consulted at https://doi.org/10.3390/electronics10212665 [205].

Chapter 3

Assessment of Cognitive Student Engagement Using Heart Rate Data in Distance Learning during COVID-19

Student engagement allows educational institutions to make better decisions regarding teaching methodologies, methods for evaluating the quality of education, and ways to provide timely feedback. Due to the COVID-19 pandemic, identifying cognitive student engagement in distance learning has become a challenge in higher education institutions. This study implemented a physiological method, specifically heart rate monitoring, to identify students' cognitive engagement during active learning activities. After heart rate data analysis, we validated five hypotheses and compared the results with a self-report questionnaire. The results confirmed that the heart rate assessment had a statistically significant difference with respect to the baseline during active learning activities, and this variance could be positive or negative. In addition, the results show that if students are previously advised that they will have to develop a new task after a passive learning activity (such as a video projection), their heart rate will tend to increase, and consequently, their cognitive engagement will also increase. This study provides input for future research assessing student cognitive engagement using heart rate parameters

This study was performed in collaboration with Escuela Colombiana de Ingenieria Julio Garavito in Bogotá, Colombia, during distance learning lessons.

3.1 Introduction

Education allows society and its territories to be transformed. As society changes, the education style must adapt to its demands [206]. Educational institutions focus their resources on achieving quality teaching and professional development for their students, who expect education to be suitable, reasonable, interactive, agreeable, and practical. Achieving these expectations directly impacts the students' engagement and becomes a matter of concern for teachers and institutions; therefore, measuring student engagement becomes a valuable and necessary tool for institutions [207]. Student engagement has been defined as the mental energy and effort students apply and invest in their academic environment [208]. Also, student engagement envelops the disposition and energy that students maintain in a learning process, persistence in the face of obstacles, and the value given to learning. A higher level of student engagement generates deep learning, active participation, and a positive response to challenges [209].

The interest in raising student engagement has led to the importance of its measurement [134], [210]. So far, in Colombia, student engagement has been measured using self-report methods, such as questionnaires, in which students directly report their perceptions; sometimes, these methods can be subjective and divert attention [11]. Furthermore, according to the literature review, this country has not yet implemented a different approach.

Higher education has been affected by the pandemic of COVID-19, generating impacts on education systems. Institutions have had to adapt their methodologies to a virtual environment and implement new teaching and online assessment strategies [211]; this transition has received different terms like remote teaching, online learning, or distance education. Some obstacles students face in this situation are an unstable internet connection, restricted access to technological tools, and inadequate space to take classes [212]. Lassoued et al. [213] have classified these difficulties into four categories: personal (self-imposed), pedagogical, technical, and financial obstacles.

This chapter presents an investigation conducted in Colombia to measure cognitive student engagement by measuring students' heart rates during COVID-19. In the United States, Darnell D. K. and Krieg P. A. [11] implemented a similar method in a group of medical students; the researchers measured cognitive student engagement using wristwatch-style monitors, which detected and recorded the heart rate of the study subjects during lecture classes that applied active learning

activities. In India, Senthil and Lin performed a study using a wireless wearable sensor to collect the heart rate of university students for measuring engagement, comparing the heart rate in a state of rest against the heart rate during active learning activities in lecture classes [214].

The structure of this chapter is as follows: first, we present a background of previous works focused on the diverse methods for measuring cognitive student engagement. Next, the methodology is divided into three phases: Research preparation (1), which describes the instruments and tools necessary for beginning the data collection. Execution of the research (2), including the collection of three types of data: quantitative heart rate data, qualitative data composed of annotations taken by the researchers during the virtual lesson development, and questionnaire data. Data treatment (3), in this phase, we proceed to data cleaning and processing for validating five hypotheses, as well as the comparative analysis of the non-self-report method vs. the self-report method using a quadrant model. Then, there is the analysis and results from the three methodology phases. And finally, the conclusions and future directions of research.

3.2 Background

Student engagement can be perceptible in the behavioral, cognitive, or affective dimensions [208]. Behavioral engagement occurs when students get involved in their learning, for example, by selecting times or places to study. Cognitive engagement happens when students make a mental effort regarding the topic they are learning; when students use deep or superficial study methods, they can identify the type of mental effort. Finally, affective engagement refers to the students' emotions, such as interest, enjoyment, or frustration [215].

Cognitive engagement is the level of psychological investment students make in the learning environment [216]. It considers mental efforts focused on reflecting, implementing strategies, and willingness to carry out the requirements for understanding complex ideas and train themselves in skills with a high degree of difficulty to master the material and achieve new knowledge [51]. Literature also describes cognitive engagement as the student's preference to perform challenging tasks and being self-regulated, a condition that leads to planning and monitoring their own learning [217]. Cognitive engagement contributes the flexibility in problem-solving and a positive attitude toward facing failures [51].

The cognitive engagement has two levels depending on the student's effort: superficial and active engagement [218]. Superficial engagement is a minimal effort in learning, like simple memorization, help-seeking, and effort-avoidant strategies; on the other hand, active engagement implies deep understanding and expertise in activities such as attention, planning, connecting, and monitoring the learning [51].

In the literature, the studies found have implemented different methods to measure student engagement evaluated from the perspective of the study subject, the student. These methods can be classified into two categories: self-report methods and non-self-report methods. One of the characteristics of the self-report methods is that the study subjects report the data directly. The most used tools are questionnaires and interviews. On the other hand, the non-self-report methods use tools that allow collecting the data without consulting directly with the study subject, such as capturing a video during class, which can later be used to analyze the emotions that the person experiences [219]. It is important to highlight that various studies have been developed for measuring student engagement from a third-party agent perspective, like a professor, a psychologist, or a researcher; these studies include teacher ratings, observation, and many others. Our study implemented a method that determines cognitive student engagement using the data measured directly from students. Consequently, the background focuses on giving examples of good practices implemented to assess student engagement by directly examining the student's point of view and behavior. In this sense, it isolates studies that assessed engagement from a third-party perspective only.

Different countries have used self-report methods; in most cases, the researchers used questionnaires or surveys created or adapted from previous investigations. Table 15 shows some studies that have used self-report methods.

Table 15: Student Engagement Self-report measurement methods

		Year of Publication			Measurement Method	Research Location	Level of Education	
Author	**Study Title**	**2010-2015**	**2015-2018**	**2018-2020**	**Method Detail**	**Country**	**School**	**College**
Lei et al. [220]	Engagement data of robotic students in a synchronous-hybrid course			X	Conducting a national survey of student engagement in a telepresence environment	USA		X

Dekhane et al. [221]	Mobile App Development to Increase Student Engagement and Problem-Solving Skills		X	The students had to develop mobile games; with a questionnaire and a pre and post-quiz, the researchers evaluated the variables.	USA		X
Awang-Hashim et al. [222]	Malaysian University Student Learning Involvement Scale (MUS- LIS): Validation of a Student Engagement Model		X	Measurement of student engagement through the MUSLIS questionnaire.	Malaysia		X
Alioon and Delialioglu [223]	The effect of authentic m-learning activities on student engagement and motivation	X		Measurement of student engagement and motivation through the NSSE- National Survey of Student Engagement and MSLQ- Motivated Strategies for Learning Questionnaire.	Turkey		X
Zhoc et al. [224]	Higher Education Student Engagement Scale (HESES): Development and Psychometric Evidence		X	Development of a case study using the HESES-Higher Education Student Engagement Scale survey.	Hong Kong		X
Ma et al. [225]	Initial Development Process of a Student Engagement Scale in Blended Learning Environment		X	Design of a survey based on the NSSE.	China		X
Balaam et al. [226]	Exploring Affective Technologies for the Classroom with the Subtle Stone	X		By means of the "Subtle stone", a hand-held orb, students inform what they feel when they press it.	United Kingdom	X	

In the USA, the researchers have used surveys and questionnaires to measure student engagement; they carried out activities different from the traditional class. In one case, Lei et al. [220] applied the National Survey of Student Engagement in a lesson composed of six people; three of them were physically present, and the other three were in telepresence. In another study [221], the students developed a mobile game using a tool (GameSalad) created by the researchers, and then they measured student engagement using a questionnaire.

In Malaysia, Awang-Hashim et al. [222] used a survey to evaluate the scale of participation in student learning at the University of Malaysia (MUSLIS) consisting of 24 items; later, they performed the data analysis using specific software. In Turkey, Alioon and Delialioglu [223] implemented m-learning material in a computer networks course to measure student engagement and motivation using the

NSSE-National Survey of Student Engagement and the MSLQ- Motivated Strategies for Learning Questionnaire, m-learning is the method that allows students to acquire certain types of knowledge anywhere and anytime utilizing wireless technologies, here is important to state that e-learning materials are designed to be watched on computers, while the visualization of m-learning materials is better on tablets or smartphones.

In China, Zhoc et al. [224] applied the HESES-Higher Education Student Engagement Scale survey, which allowed them to evaluate five facets of student engagement: academic engagement, cognitive engagement, social engagement with classmates, social engagement with teachers, and affective engagement. Another study applied a survey to measure student engagement, Ma et al. [225] used a guide for the formulation of projects of innovation and technological development in a mixed environment, that is, the combination of face-to-face and virtual class; the survey evaluated three modules: behavioral, cognitive and emotional behavior.

Although questionnaires and surveys are the most common tools, some researchers have used other tools; for instance, in the United Kingdom, Balaam et al. [226] developed a handheld orb named Subtle Stone for implementing an interactive method with the students, the study subjects, had to press the Subtle Stone to indicate the emotion that they were experimenting in a class.

Table 16 presents some studies that have used non-self-report methods in different countries. These methods usually collect and analyze data on the physiological characteristics of the study subjects, such as facial expressions, eye movement, and heart rate.

Some studies conducted in China, the USA, Canada, and Ireland analyze facial expressions to determine factors such as emotions or student engagement. In Hong Kong, Zeng et al. [219]developed an analytical system that recognizes emotions through facial expressions, named EmotionCues; they use a camera and software that detects which emotion a student is expressing. In another study conducted in China, Zhang et al. [210] identified affective states such as boredom, confusion, and engagement through a facial recognition system. In the USA, Alkabbany et al. [227] recorded a video during a reading of 10 to 15 min; this video focused on the angle of the posture of the face and the gaze, after, the researchers analyzed these characteristics to identify student engagement; in another study also carried out in the USA, Whitehill J. et al. [134] analyzed facial expressions using Machine Learning to determine the level of engagement. In Canada, Sakulchit et al. [228]

identified the emotions that children experienced before, during, and after taking a blood sample through facial expressions and, in the case of Ireland, Farrell et al. [229] using an application, analyzed the subject's head posture to determine if the student was looking at the screen. Thus, they detected the person's emotional state, finally allowing them to assess student engagement.

Table 16: Student Engagement Non-Self-report measurement methods

		Year of Publication			Measurement Method	Research Location	Level of Education		
Author	**Study Title**	**2010-2015**	**2015-2018**	**2018-2020**	**Method Detail**	**Country**	**School**	**College**	**Other**
Zeng et al. [219]	EmotionCues: Emotion-Oriented Visual Summarization of Classroom Videos			X	Recognize emotions by analyzing facial videos.	Hong Kong	X	X	
Zhang et al. [210]	A Novel End-to-end Network for Automatic Student Engagement Recognition			X	Face recognition with I3D- processing of 3D images or videos	China		X	
Alkabbany et al. [227]	Measuring Student Engagement Level Using Facial Information			X	Detect facial actions (head posture, gaze)	USA		X	
Farrell et al. [229]	Real Time Detection and Analysis of Facial Features to Measure Student Engagement with Learning Objects			X	An application identified the emotional state and the position of the head.	Ireland			X
Whitehill et al. [134]	The Faces of Engagement: Automatic Recognition of Student Engagement from Facial Expressions	X			They collect facial expressions and analyze them with machine learning (ML), which detects high or low interaction.	USA		X	
Sakulchit et al. [228]	Evaluation of Digital Face Recognition Technology for Pain Assessment in Young Children			X	A program, API (Application Programming Interface), analyzed images taken of the face and identified the emotions of the study subjects.	Canada			X
Herpich et al. [230]	Mobile Augmented Reality impact in Student Engagement: an Analysis of the			X	They measured student brain signals to see the impact of augmented reality on	Brazil		X	

	Focused Attention dimension		student engagement.			
Hayashi et al. [231]	A Quantitative Study on Learner Engagement Evaluation: Integrated Analysis of Biosignals Including Pulse Wave and Eye Movements	X	Measuring eye movement with three electrodes built into glasses.	Japan	X	X
Darnell and Krieg [11]	Student engagement, assessed using heart rate, shows no reset following active learning sessions in lectures	X	They measured students' heart rates to identify cognitive students engagement.	USA		X

Other physiological characteristics analyzed in the studies presented include the study of brain signals and eye movement. In Brazil, Herpich et al. [230] measured the signals emitted by the brains of students when interacting with educational technology. In Japan, Hayashi et al. [231] used lenses with integrated electrodes to analyze the user's eye movement and thus determine student engagement.

Finally, the heart rate is another physiological characteristic researchers have used to measure student engagement [11], [214]. In a study performed in the United States, Darnell and Krieg [11] measured student engagement, specifically cognitive engagement, analyzing the students' heart rate. Researchers analyzed the heart rate behavior using wristwatch-style monitors during active learning activities.

Heart rate has been a tool widely used for identifying and monitoring emotions, attention, autonomic process, and mental conditions [232]–[236]; heart rate is associated with the autonomic nervous system, which responds to a stimulus or resting states [235], [237]. Emotions have three components: cognitive, physiological, and behavioral [236]. These components allow researchers to use the heart rate to measure more advanced factors like cognitive engagement [11], [237]. Cognitive engagement can be determined through the heart rate since the exposure to stimulus or tasks activates neural mechanisms and, consequently, triggers an acceleration or deceleration in the heart rate, which has been an indicator of alertness and drowsiness [92], [93], [238]. The advantages of using heart rate include it is non-invasive, easy, and cheap to get [235], [236], experiments with heart rate are simple to set up and can be used in conjunction with other biometric measures like facial expressions and respiration [93], [239]. The disadvantages associated with the heart rate are the conditions of the environment under which the data collection occurs since they are challenging to eliminate and also the response

time to a stimulus is long; these two points generate more uncertainty [232], [240], [241].

Active learning activities allow student engagement to be improved and induced [242], [243]. The concept of active learning refers to activities that induce students into a thinking process about new information and connect it with experience or knowledge [242], [244]. There is a great variety of activities that can be considered active learning, such as discussion in small groups, peer activities, individual activities that require mental effort, interactions, study cases, problem resolution, laboratories, quizzes, and games, all of them have to guarantee that students think effectively [242]–[246]. The advantages include that students feel more secure sharing their ideas in small groups, developing critical thinking, retaining new knowledge, developing communication and leadership skills, and feeling more motivated and interested [242], [244]–[247].

In Colombia and Latin America, as some researchers stated, the investigations regarding education and student engagement have focused on the following topics: study habits and motivation for distance learning [248], academic dropout and its relationship with the student's conditions and the organizational context of the academic institution [249] the relationship between student engagement and academic performance determined through the academic average [250], and the relationship that emotional intelligence and happiness orientation have with student engagement [251].

Other research examines the opinion of students in schools regarding how they experience student engagement after conducting, recording, and analyzing surveys [252]. Bertel-Narvaez et al. [206] performed a literary review of education in Latin America, highlighting that the motivation of learning is a fundamental aspect of developing research in Latin America. Studies and research developed in Colombia have used traditional methods such as interviews, surveys, questionnaires, and the corresponding analysis. However, the studies have not yet used more advanced techniques to measure student engagement with physiological characteristics in this country.

In Colombia, the current studies have not implemented a method using physiological characteristics to measure cognitive engagement. This work developed exploratory research similar to the analysis proposed in the United States by Darnell and Krieg [11] and adapted for this study during the pandemic. We used

the heart rate for measuring cognitive student engagement. In some studies, the heart rate is also used for determining the emotional aspect [93], which means that emotional and cognitive engagement generates a variation in the heart rate. For that reason, a good way to differentiate these dimensions is through the activity or stimuli to which the student is exposed. In this study, we selected active learning activities, which are focused on activating cognitive engagement. For collecting data, the students used a heart rate band linked to a mobile application while participating in virtual lessons that contained active learning activities; every student collected her or his heart rate during four lessons; the total data collection took three months. This research took place at Escuela Colombiana de Ingenieria Julio Garavito in Bogota, Colombia, in a sample of 20 students, from which we discarded four students after data cleaning.

3.3 Materials and Methods

This study adopted the methodology developed by Carrasco and cited by Vinan et al. [253]. It consists of three phases (Table 17); the first phase entails the research preparation, the second phase is the execution of the research, and the third phase regards the data treatment. The objective of this study was to determine the cognitive student engagement using the heart rate as the primary measurement tool and a questionnaire as a complementary tool.

Table 17: Research methodology

Phase 1	Phase 2	Phase 3
Research Preparation	**Execution of the Research**	**Data Treatment**
• Active learning activities. • Participants. • Heart rate band preparation.	• Quantitative data (non self-report method). • Qualitative data of annotations. • Qualitative data of the questionnaire (non self-report method).	• Data Cleaning. • Data processing. • Non-self-report method vs. self-report method

The development and detail of each phase are described below.

3.3.1 Phase 1. Research Preparation

This phase consists of four activities to prepare instruments and tools necessary for data collection. Figure 16 details each activity.

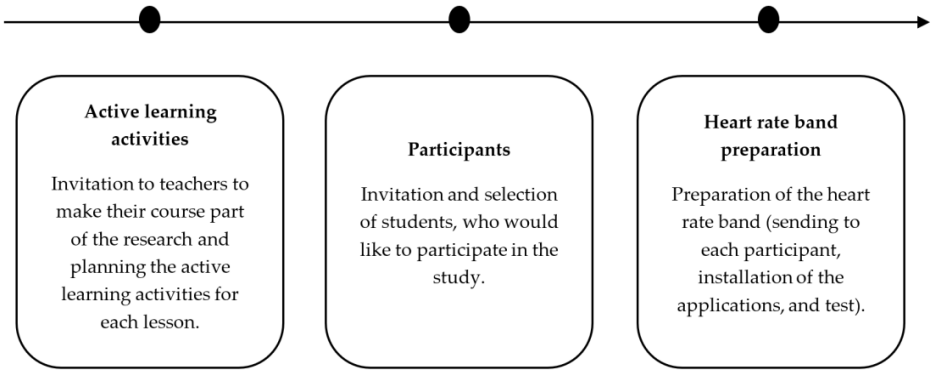


Figure 16: Research preparation

Below, we explain the considerations made for developing each activity.

3.3.1.1 Active Learning Activities

All the activities planned with the professor include active learning activities performed in virtual lessons during COVID-19. In each lesson, they developed the method Think Pair Share proposed by Kaddoura [254] and adapted it to this study, which we detail below:

1. Think: the professor asked a question, observation, case study, or video that induced the student to think. The student had to think and write down the answers.
2. Pair, partner, or individual: students had to share the answer with one or two partners to analyze each one and reach a consensus on the best solution to the question asked. When performed individually, the student must complete an activity as instructed by the professor.
3. Share: then, the professor asked each pair of classmates to share their answers with the whole lesson. However, in some cases, the students did not share their answers but gave the solution to the professor directly.

3.3.1.2 Participants

The following characteristics were considered for selecting the participants:

1. They must be of legal age.
2. They must have a compatible cell phone.
3. They must live in Bogota or neighboring cities.
4. Students must participate voluntarily.

In this study, we measured the heart rate of 20 students, from which we discarded four students after cleaning the data. We defined the number of participants after reviewing the sample used in similar studies carrying out non-self-report methods (Table 18).

Ethical considerations were considered following the guideline given by Escuela Colombiana de Ingenieria Julio Garavito, the Data Processing Policy Department reviewed and approved the document of data treatment used in this study, which posteriorly was signed by each student. The following ethical guidelines were implemented in the research:

1. We preserved the participants' anonymity.
2. Each participant's personal data was used only for the research objectives, and we obtained the student's permission to use these data, keeping the real name confidential.
3. The activities developed in each lesson avoided exposing participants to mental stress.
4. We informed participants about the correct use of heart rate bands, a tool that is not dangerous or risky.
5. We gave each participant an informed consent with the corresponding information about how the research will be developed.

Table 18: Number of participants in studies of non-self-report methods

Study	Number of Participants
EmotionCues: Emotion-Oriented Visual Summarization of Classroom Videos	Case 1: 15 children Case 2: 13 students
Multimodal affect recognition in learning environments	8 children
Measuring Student Engagement Level Using Facial Information	14 students
Mobile Augmented Reality Impact in Student Engagement: An Analysis of the Focused Attention Dimension	5 students
A Quantitative Study on Learner Engagement Evaluation: Integrated Analysis of Biosignals Including Pulse Wave and Eye Movements	Case 1: 6 students Case 2: 10 students
Artificial neural networks-based classification of emotions using wristband heart rate monitor data	12 individuals

3.3.1.3 Heart Rate Band Preparation

This investigation used heart rate bands, which can measure the heart rate with a frequency of one minute; these have a Photoplethysmography (PPG) heart rate sensor, which applies low-intensity infrared (IR) light on the skin. An optical sensor measures light reflection, which changes depending on the blood flow through the illuminated spot. Since blood flow changes during a heartbeat, it is possible to measure the heart rate.

The considerations for preparing the heart rate band were the following:

1. Each course was composed of 5 or 4 students who participated in the research.
2. The heart rate band must be delivered to each participant.
3. Each participant must install the heart rate recording app on their cell phone.
4. To verify the correct functioning of the heart rate band, the students made a preliminary test.

3.3.2 Phase 2. Execution of the Research

We divided the execution of the investigation into three categories, composed of the data collected: quantitative data, qualitative data of annotations, and qualitative data from the questionnaire. The quantitative data (obtained through a non-self-report method) refers to heart rate data collected through the heart rate app during the development of each virtual lesson. The annotations of qualitative data refer to the data collected by the researchers while attending each lesson and taking note of the activities carried out and their respective times. Finally, the qualitative data refers to the questionnaire (self-report method) that each student filled out at the end of each lesson, which evaluated the cognitive student engagement. Figure 17 presents each data category collected in this phase. Below, we explain the conditions required in each data category.

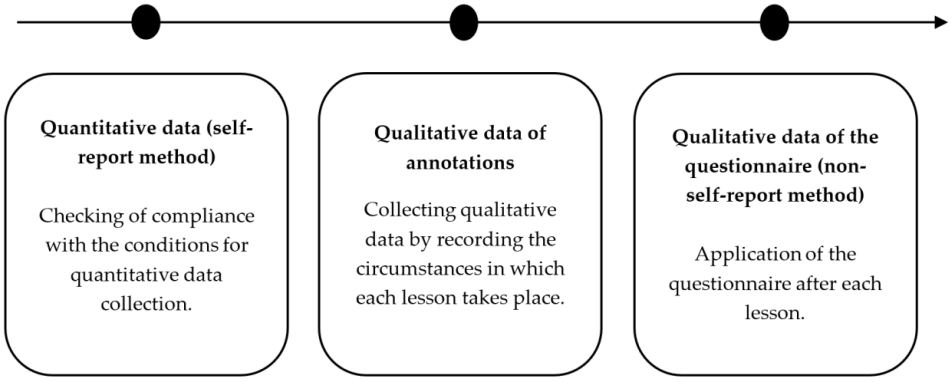


Figure 17: Execution of the investigation

3.3.2.1 Quantitative Data (Non-Self-Report Method)

The conditions verified in the quantitative data collection were the following:

1. The students must wear the heart rate band five minutes before starting the virtual lesson.
2. The students must activate and connect the Bluetooth between the cell phone and the heart rate band.
3. Participants must follow the instruction for measuring the baseline heart rate; it refers to each participant's heart rate during a rest state.
4. Participants must connect to the lesson on time.
5. The participants agreed to send the data after finishing each lesson.

3.3.2.2 Qualitative Data of Annotations

To collect annotations and qualitative data, the researchers considered the following aspects:

1. Identify when the virtual lesson started, splitting the greeting from the main topic.
2. Recognize when active learning activities start and finish.
3. Take note of the moment when participants intervened.
4. Identify activities that can generate some emotions in the participant not planned by the research.
5. Record the exact time when the virtual lesson ends.

3.3.2.3 Qualitative Data of the Questionnaire (Self-Report Method)

A questionnaire is a self-report tool to measure student cognitive engagement. However, using this method will allow us to compare the student report and the

results obtained with the measurement of heart rate and help to identify factors that may affect the student's heart rate behavior during lessons.

As described above, the participants filled out a questionnaire after completing each virtual lesson; the main objective was to identify the students' cognitive engagement reported, allowing us to compare the participants' answers and the heart rate behavior.

To identify student cognitive engagement in different contexts, the queries in the questionnaire were selected following three studies, which applied questions focused on measuring student engagement. For the questionnaire design for this study, we selected questions focused on measuring student cognitive engagement.

- Study one: Exploring Factors and Indicators for Measuring Students' Sustainable Engagement in e-Learning [255]

In this research, through a questionnaire, they analyzed six factors in student engagement in the e-learning environment: factor 1. psychological motivation, factor 2. peer collaboration, factor 3. cognitive problem solving, factor 4. interactions with instructors, factor 5. community support, and factor 6. learning management. For our study, we selected and adapted factor 3 (Cognitive problem solving).

- Study two: Examining engagement in context using experience-sampling method with mobile technology [215]

The following measures were applied in the above survey: study time, study location, reasons for study, behavioral engagement, cognitive engagement, self-efficacy, academic motivation, and prior academic achievement. For our questionnaire, we adapted the measures used in cognitive engagement.

- Study three: Initial Development Process of a Student Engagement Scale in Blended Learning Environment [225]

In this study, Ma et al. [225] designed and constructed a student engagement scale framework in higher education during a blended learning environment. They evaluated the three dimensions of student engagement (cognitive, behavioral, and emotional). For our questionnaire, we selected the items used in cognitive student engagement.

Table 19 presents the template used in the questionnaire, the self-report method used in this study, which the students filled out after finishing each virtual lesson. We used a Likert scale from 1 to 5 (1: totally disagree and 5: totally agree) to rate each item. The interpretation given to this scale related to cognitive student engagement was the following: An answer of 1 indicated a low cognitive engagement, an answer of 5 indicated a high cognitive engagement, and an answer of 3 was taken as a neutral position regarding the question.

Table 19: Self-report method

	Questionnaire
1	I can deduce new interpretations and ideas from the knowledge I have learned in today's lesson.
2	I can deeply analyze thoughts, experiences, and theories about the knowledge I have learned in today's lesson.
3	I can judge the value of information related to the knowledge learned in today's lesson.
4	I tried to approach the topic of today's lesson with a new perspective.
5	In today's lesson, I tried to learn new material by mentally associating new ideas with similar ideas that I already knew.
6	While learning new concepts in today's lesson, I tried to think of practical applications.
7	I made sure I understood the material I studied in today's lesson. (I am aware of what material I understood or did not understand).
8	In today's lesson, I tried to memorize the answers to the questions in the study guides for the tests.
9	To understand the technical terms, I memorized the definitions provided in the texts or today's lesson notes. (I'm trying to memorize the vocabulary for this lesson).
10	I tried to write down exactly what my instructor said during the lectures in today's lesson.
11	I used what I have learned to solve practical problems in today's lesson.
12	I make connections between the things that I have learned in today's lesson.
13	I tend to apply the knowledge I have learned in lesson to real problems or new situations.
14	When I learned new material, I summarized it in my own words.
15	I mentally combined different pieces of information from the course materials in an order that made sense to me.
16	In doing the readings for the lesson, I tried to figure out what part of the reading would be on the test. (I'm studying the course materials to get the information needed for the test).
17	I study ideas exactly as they are expressed in lesson or in my readings.
18	Establish a learning plan to be able to direct my activities in the lessons.

19	I have clear learning objectives at each stage of the course.
20	I make good use of my study time for this course.
21	I connect what I have learned in this course with another subject.
22	When I read learning materials from the course, I ask myself questions and think about a topic.
23	I use what I have learned from homework and tests to promote my next learning step.
24	I think about what I have already learned to understand a new course topic.

3.3.3 Phase 3. Data Treatment

This phase included three activities that allowed us to perform the data treatment (Figure 18). The first consisted of cleaning data, the second entailed data processing, and the last compared the non-self-report method with the self-report method.

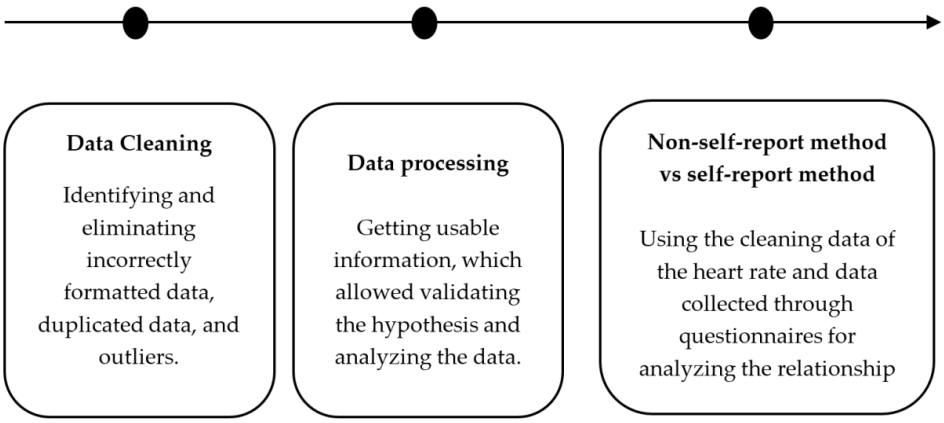


Figure 18: Data treatment

3.3.3.1 Data Cleaning

First, we organized the data into three categories: participants, lessons, and activities. The criteria used for cleaning the data were the following:

1. Transform the date and time data into a single format.
2. All participants must have data from at least three virtual lessons; otherwise, it is discarded.

3. We normalized the data and filtered those that were greater than three standard deviations (3SD). Then, we compared the total data with the resulting data after applying the criterion of 3SD and decided to delete data that removed less than 15% of the total data. We considered this criterion and percentage under the following categories: each participant in each lesson.
4. We cleaned the data that did not have modifications in numeral 3 (the normalization with 3SD). We analyzed each participant's activity in each lesson and eliminated the atypical data.

3.3.3.2 Data Processing

Intending to have a general view of data, we applied a clustering of all data. After, we processed and organized the data to verify the following hypothesis:

- Hypothesis 1. The heart rate may increase during an active learning activity or rest and then return to the mean level.
- Hypothesis 2. The heart rate decreases from the beginning to the end of the lesson.
- Hypothesis 3. The decrease in heart rate is biphasic, further decreasing during the early stages of the lesson.
- Hypothesis 4. The heart rate decreases at the beginning and increases at the end of the lesson.
- Hypothesis 5. The heart rate decreases in passive learning activities like watching a video.

For each hypothesis, we developed the following data processing:

For Hypothesis 1, we selected and labeled active learning activities in each lesson for each participant; we also labeled activities before and after each one, considering only those corresponding to theoretical explanation, beginning of a lesson, or end of a lesson. Subsequently, we plotted the mean heart rate before, after, and during each active learning activity using a data science platform.

For Hypothesis 2, we plotted the heart rate against the time for each participant in each lesson. We applied linear regression to identify if the heart rate trend decreased or increased.

For Hypothesis 3, we divided the data into two sections to analyze the biphasic behavior. We showed the first 20 minutes of each lesson against the next 70

minutes. We plotted the heart rate against time in each section; finally, we applied linear regression. For Hypothesis 4, we selected the first and last minutes of each lesson, ranging between 2 to 10 min, to analyze the behavior at the beginning and end of each lesson. The time range is variable since each lesson started or finished the topic and activities at a different time. Then, we graphed each time range and applied linear regression to identify the behavior at the beginning and end of each lesson. And for Hypothesis 5, we performed the same processing as the first hypothesis, with the difference that we selected and labeled the passive learning activities at this phase.

3.3.3.3 Non-Self-Report Method vs. Self-Report Method

In the research developed by Nonis et al. [135], the results suggested combining two types of methods for measuring engagement and proposed to combine the User Engagement Scale questionnaire with an additional physiological measurement (a facial expression recognition system). In this section, for analyzing the behavior of quantitative data of the heart rate (non-self-report method) against qualitative data of the questionnaire (self-report method), we employed a quadrant model to show the variation of these two data types (Figure 19).

For quantitative data, we calculated the mean heart rate for each participant and subtracted the heart rate baseline to identify whether there was a positive or negative variation. For the qualitative data of the questionnaire, we calculated the mean response to the questions of questionnaires filled out in each lesson; each question indicates a high or low level of student cognitive engagement, thus if the student's mean response was below 3, it indicated a low engagement, and if it was above 3 it indicated a high cognitive engagement. Quadrant I represented a positive variation of the heart rate and a high level of cognitive engagement reported in the questionnaire by students, quadrant II indicated a positive variation of the heart rate and a low level of cognitive engagement reported in the questionnaire by students, quadrant III represented a negative variation of the heart rate and a low level of cognitive engagement reported in the questionnaire by students. Finally, quadrant IV indicated a negative variation in the heart rate and a high level of cognitive engagement reported in the questionnaire by students.

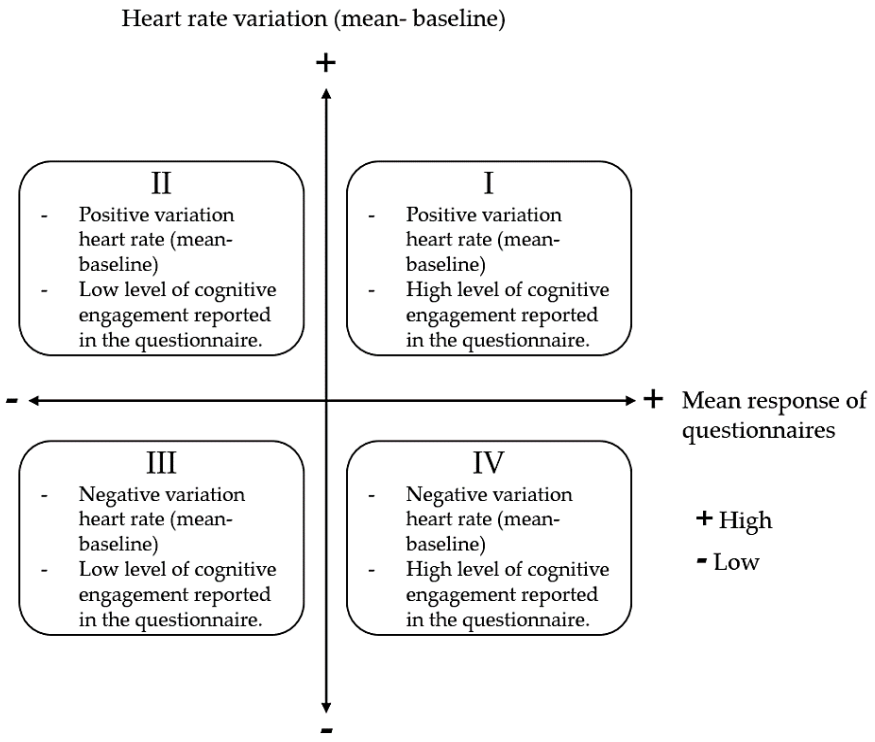


Figure 19: Quadrant model of heart rate variation vs. mean response of questionnaires

3.4 Analysis and Results

3.4.1 Phase 1. Research Preparation

Four groups of five students in the Human Talent Management course participated in the research led by two professors. The activities planned and developed in each lesson followed the method: Think Pair Share [254]. Also, other activities considered were online quizzes, group activities, activities in pairs, and individual activities. The lessons were in remote teaching using a virtual communication platform and online programs to develop the activities.

The 20 participants belong to the industrial engineering program; Figure 20 presents the characteristics associated with them:

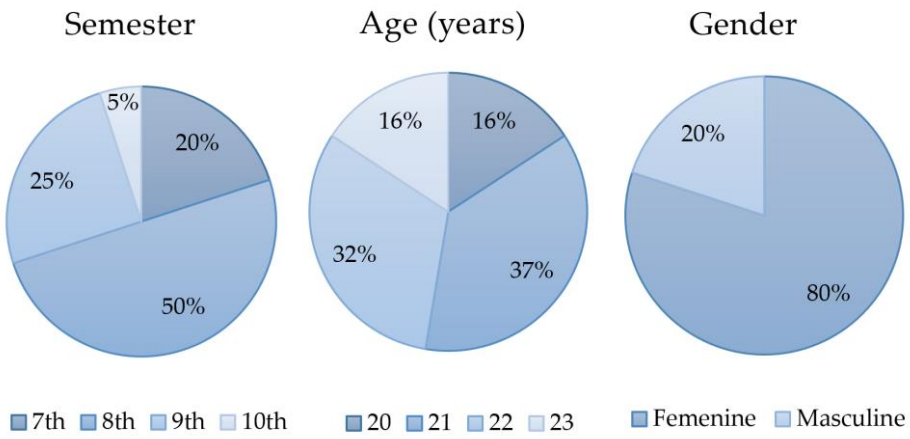


Figure 20: Participants' Information

All participants followed the instructions and conditions for preparing the heart rate band. However, due to compatibility and connection issues, we discarded the data from participants 0 and 19.

3.4.2 Phase 2. Execution of the Research

Using the heart rate band, we measured each participant's heart rate during the virtual lessons. We took note of different conditions that could alter the student's heart rate and the moment in which the professor developed active learning activities. Also, we collected the baseline heart rate of each participant (Table 20). In this study, we used the baseline for identifying the heart rate response to activities developed in each lesson; the difference between the baseline and the heart rate could be negative or positive, depending on the engagement of each participant. The behavior of the heart rate compared with the baseline is the response to a stimulus, according to the study of Siennicka et al. [235]. We do not show the baseline heart rate of four participants (participant 0, participant 9, participant 18, and participant 19) in Table 20 for the reasons explained above. In the cleaning data section, we will explain why participants 9 and 18 were also discarded.

On the other hand, we applied the questionnaire described in the methodology; we used a Likert scale to rate each item as follows: (1) totally disagree, (2) in disagreement, (3) partially agree, (4) I agree, and (5) totally agree. In Table 20, also we show the mean according to the response given by participants in the questionnaire.

Table 20: Participants' Questionnaire mean response and baseline heart rate

Participant	1	2	3	4	5	6	7	8	10	11	12	13	14	15	16	17
Baseline Heart Rate (bpm)	77.2	74.8	70.3	73.3	72.9	77.8	76.9	74.8	78.9	86.0	77.3	71.2	70.7	80.4	75.0	75.0
Questionnaire Mean Response	3.95	2.72	2.50	4.68	3.83	3.17	3.58	3.42	4.26	3.13	4.42	3.51	3.10	3.94	3.83	3.99

3.4.3 Phase 3. Data Analysis

3.4.3.1 Data Cleaning

Applying the criteria described in the methodology, we transformed the data into the same time format requested by the data science platform; we used this tool to perform some data cleaning and processing steps. We discarded two participants because they had data from less than three lessons (participant 9 and participant 18). Then, we applied the normalization criterion to the participants and lessons shown in Table 21. Finally, we analyzed the behavior of each participant in each activity and eliminated the outliers.

Table 21: Normalized and discarded data under the criteria of 3SD

	Part 1	Part 2	Part 3	Part 4	Part 5	Part 6	Part 7	Part 8	Part 10	Part 11	Part 12	Part 13	Part 14	Part 15	Part 16	Part 17
Lesson 1	X	X		X	X		X									
Lesson 2		X					X			X		X	X	X		
Lesson 3						X							X			
Lesson 4			X	X	X						X	X	X			X

3.4.3.2 Data Processing

Before analyzing each hypothesis, we clustered all the data dividing each group to identify the general and predominant behavior of the heart rate. First, we applied the elbow method. We obtained that, in all groups, the best value of K was seven, and then we proceeded to the data clustering.

Table 22 shows the cluster for each group, the number of items classified in each cluster, and the centroid based on the heart rate. We presented the table organized in descending order according to the centroid, highlighting the two

clusters with the most items. The clusters highlighted indicate the predominant behavior of the heart rate in each group, varying from between 66 and 77, except for Group 1, which is between 70 and 82. This behavior shows that the predominant data was not in the extremes, which contained a minority of items.

Figure 21 shows the distribution of items in each cluster for each group. In each graph, the behavior of each cluster is similar in each lesson. Although each participant had a different baseline, it did not alter the classification in the clustering. For this reason, we were able to perform a general analysis of the data. We conducted an ANOVA test afterward; for better data treatment, we conducted additional analysis by categorizing the heart rate according to participants, lessons, and activities.

Table 22: Number of items and centroid for each cluster

GROUP 1			**GROUP 2**			**GROUP 3**			**GROUP 4**		
Cluster	**Number of Items**	**Centroid HR (bpm)**	**Cluster**	**Number of Items**	**Centroid HR (bpm)**	**Cluster**	**Number of Items**	**Centroid HR (bpm)**	**Cluster**	**Number of Items**	**Centroid HR (bpm)**
4	99	60.2	1	218	63.1	6	149	58.1	1	86	60.7
3	247	66.3	**5**	**416**	**69.9**	**0**	**402**	**66.8**	**3**	**243**	**69**
6	**428**	**70.9**	**0**	**341**	**76.4**	**4**	**429**	**74.9**	**0**	**262**	**75.8**
1	340	75.9	3	241	82.2	2	306	82.9	2	197	81.3
0	**360**	**81.6**	6	158	88.5	1	310	91.7	6	135	87.5
5	337	87.8	4	69	96	3	217	99.2	4	81	94.9
2	200	95.5	2	18	107.9	5	59	109.4	5	27	105.6

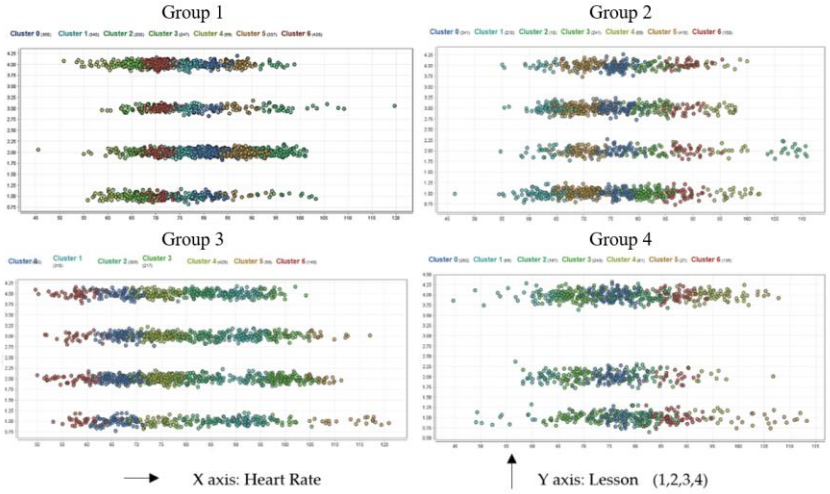


Figure 21: Cluster Items Distribution by group

For each hypothesis, after applying the data processing, we obtained the following results:

- Hypothesis 1.

After selecting and labeling each active learning activity's mean heart rate (MHR) with its activities before and after, we obtained four behaviors, which described the mean heart rate before, during, and after an active learning activity. We show an example of each behavior in Figure 22.

- Behavior one (low MHR-high MHR-low MHR): The behavior of the mean heart rate before and after the active learning activity is lower than the behavior during this activity. This behavior coincides with H1.
- Behavior two (high MHR-low MHR-high MHR): The behavior of the mean heart rate before and after the active learning activity is higher than the behavior during this activity. This behavior is contrary to H1.
- Behavior three (low MHR-high MHR-high MHR): The behavior of the mean heart rate before the active learning activity is lower than the behavior during this activity, while the behavior of the mean heart rate after this activity is higher than the active learning activity. This behavior presents an increase during an active learning activity as described by H1, but then, after the MHR, it continues to increase.
- Behavior four (high MHR-low MHR-low MHR): The behavior of the mean heart rate before the active learning activity is higher than the behavior during this activity, while the behavior of the mean heart rate after this activity is lower than the active learning activity. This behavior does not correspond with H1.

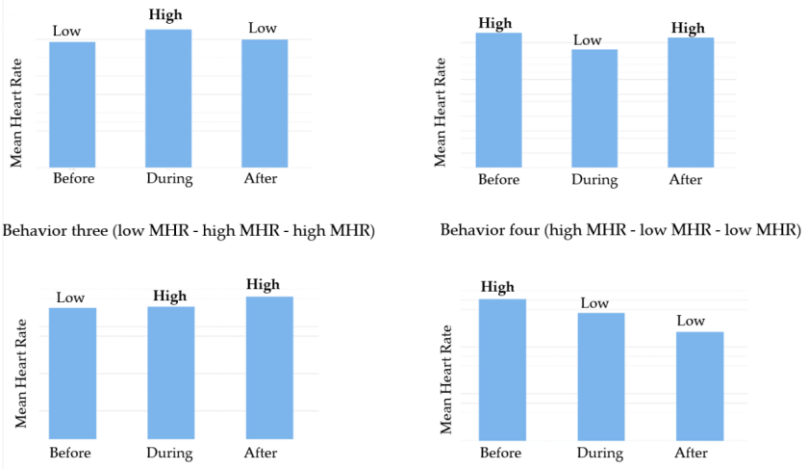


Figure 22: Mean Heart Rate behavior

For this analysis, we examined 58 active learning activities; Table 23 presents the results obtained in each behavior. It is important to note that the activities we considered before an active learning activity were the *theoretical explanation*, the *beginning of a lesson*, or the instruction given by the professor. If the activity is a theoretical explanation, the student could be in a rest state; thus, the heart rate may be lower than in an active learning activity. On the other hand, if the activity is at the beginning of a lesson, the heart rate may vary due to external factors depending on each student's activity before starting the lesson. Finally, if the previous activity is the *instruction given by a professor*, the student can be attentive without doing any activity that involves deep learning. These three activities have in common that they are not active or passive learning activities; for this reason, they can be grouped for the analysis of H1.

Table 23: Active learning activities according to each behavior

Behavior	Number of active Learning Activities	Percentage
Behavior one (low MHR-high MHR-low MHR)	24	41.40%
Behavior two (high MHR-low MHR-high MHR)	13	22.40%
Behavior three (low MHR-high MHR-high MHR)	7	12.10%
Behavior four (high MHR-low MHR-low MHR)	14	24.10%
	58	100%

Behavior one (low MHR - high MHR- low MHR) coincides with H1. As shown in Table 23, 41.4% of the activities presented this behavior, which has the highest percentage compared to the other behaviors. On the other hand, behavior two (High MHR-low MHR- high MHR) represents the contrary situation to H1. The main reason why this situation could happen was the activity: interaction between students and professor, which could generate an immersive state in the students, causing a decrease in their heart rate.

Behavior three (low MHR - high MHR - high MHR) is not common, and it is consistent with the results of the study of Darnell and Krieg. They stated that after an active learning activity, the heart rate did not continue to increase but returned to the behavior it had before this activity [11]. Finally, behavior four (high MHR - low MHR - low MHR) represents a resting state due to the heart rate decreasing during an active learning activity. This result indicates that the participant did not need to make a significant cognitive effort because of previous knowledge and clarity regarding the discussed topic.

Since MHR behavior during an active learning activity is the most relevant factor in this study, we applied an ANOVA (Table 24) with $p < 0.05$ between two variables: the baseline heart rate and the mean heart rate during active learning activities. If the value F is greater than the critical value for F, it implies that the means of the two variables are significantly different.

Table 24: ANOVA - Active learning activities

Active Learning Activity	F	Critical Value for F	Had Heart Rates Statistically Significant Differences?
Quiz	0.181	3.890	No
Discussion of a topic in group or pair	37.492	3.865	Yes
Share responses to an activity	11.834	3.910	Yes
Individual activity	24.341	3.857	Yes
Interaction between students and professor	6.801	3.860	Yes

Except for the quiz, all active learning activities had statistically significant differences in heart rate when participants developed these activities compared to each participant's baseline. The case of the quiz had a particularity, a set time was given to finish it, but some participants could finish earlier, so they could carry out other activities in the remaining time, such as taking a break; this condition could be the main reason why in the ANOVA this activity was not statistically significant.

Overall, we partially accept H1 adapting the initial approach to the following: the mean heart rate significantly varies with an active learning activity, indicating cognitive engagement in the student experiment. This approach is also supported by the statement made by Maison and Oleksy, "heart rate is useful in the detection of cognitive attention because it changes when cognitive attention is directed to a particular situation" [256].

- Hypothesis 2.

For this hypothesis, we graphically represented the heart rate values of each virtual lesson and applied linear regression. In each graph, it was possible to identify if the heart rate trend (HRT) increased or decreased during each lesson (Figure 23). We were able to identify two behaviors:

- Behavior one (HRT decreased): The heart rate decreased from the beginning to the end of the lesson. It corresponds with H2.
- Behavior two (HRT increased): The heart rate increased from the beginning to the end of the lesson. It is contrary to H2.

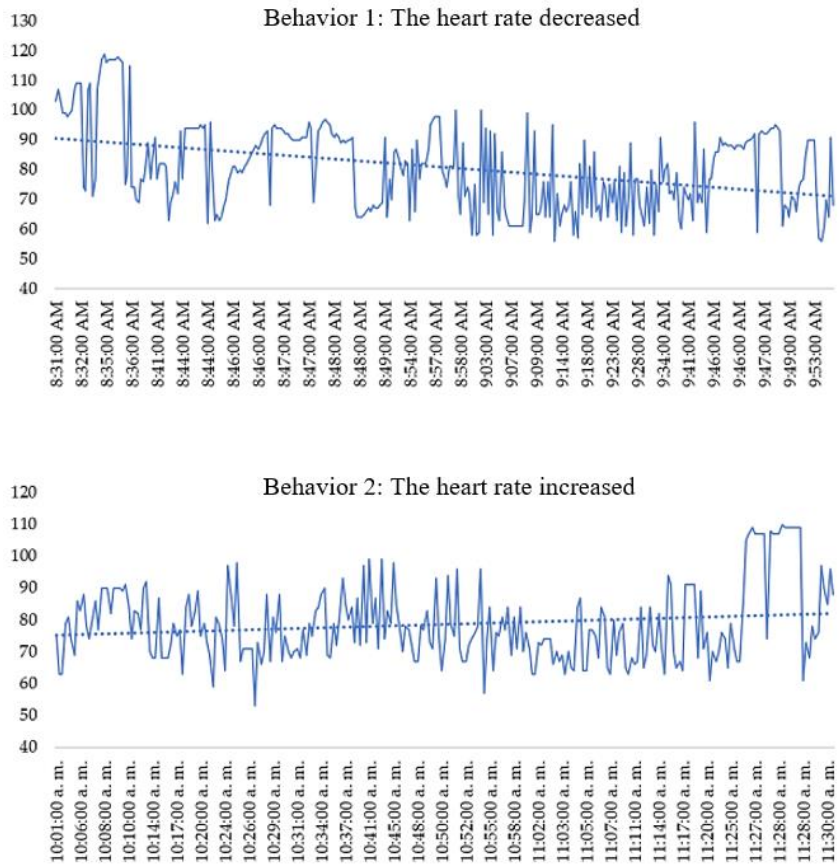


Figure 23: Heart rate trend (bpm). It decreased or increased from the beginning to the end of the lesson

In total, we evaluated 15 lessons; Table 25 shows the summary of each behavior. The expected trend of the heart rate was not evident in all lessons; although in the study of Darnell and Krieg, the authors found a decreasing trend among all the lecture lessons analyzed [11], the results we obtained in virtual lessons suggest that the trend in heart rate from the beginning to the end of the lesson may depend on external or internal factors. The external factors are related to connectivity problems or the environment in which the participant takes the lesson; the internal factors are related to the moment in which the students develop active learning activities and their duration, either at the beginning, in the middle or the end of the class. For these results, we partially accept H2 with the following adaptation: the trend of the heart rate from the beginning to the end of the lesson depends on external and internal factors, the internal factors are linked with the

active learning activities, mainly the duration and the moment in the lesson that the professor develops them.

Table 25: Heart rate trend

Heart Rate Trend	Number of Lessons	Percentage
Behavior one (HRT decreased)	9	60%
Behavior two (HRT increased)	6	40%
	15	100%

- Hypothesis 3.

For this hypothesis, we selected the virtual lessons that presented a decrease in the heart rate trend according to H2; after that, we divided the data into two sections: the first 20 min of each lesson against the next 70 min. Figure 24 shows an example of a lesson divided into two sections with its linear regression.

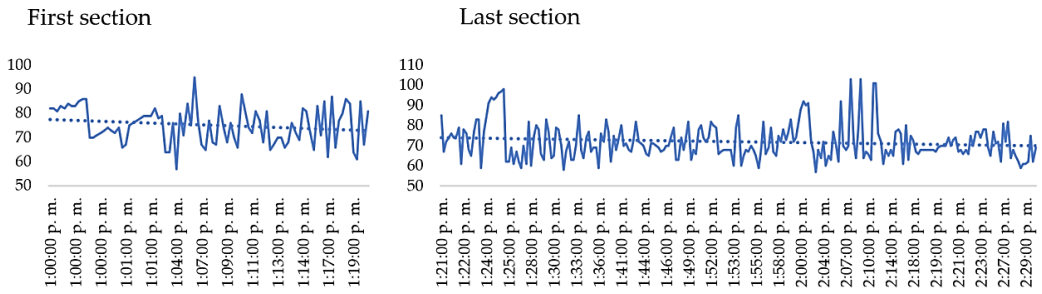


Figure 24: Biphasic behavior during a lesson

A negative slope means a decrease in the heart rate trend, in Table 26, we show the slope of each section of the lessons analyzed and its correspondence with H3; for the correspondence, we evaluated if the first and last sections had a negative heart rate trend and if the slope in the first section was minor to the slope in the last section, which indicated a further decrease during the early stages of the lesson.

Table 26: Trend of first and last section for each lesson

Lesson	Slope			Correspondence with H3
	General	First Section	Last Section	
1	-0.019	-0.053	-0.017	Yes
2	-0.0055	0.028	-0.0098	No
3	-0.0027	-0.0579	0.0132	No

4	-0.0047	-0.0483	-0.0086	Yes
5	-0.0046	0.0181	0.0112	No
6	-0.058	-0.1459	0.0143	No
7	-0.0157	-0.0563	-0.0085	Yes
8	-0.0051	-0.0666	-0.0228	Yes
9	-0.011	0.3008	-0.0115	No

We show the summary of correspondence with H3 of the 15 lessons in Table 27, which displays the nine lessons analyzed in Table 26 and the six lessons that had an increase in H2 and which do not correspond with H3 (Table 25). H3 has a strong dependency on H2 since it requires a decrease in heart rate throughout the lesson, a condition that was not met in all lessons; for this reason, we included the six lessons for the H3 correspondence analysis. Since 73% of the lesson did not show the behavior expected, we reject H3.

Table 27: Correspondence with hypothesis 3

Correspondence with Hypothesis 3	**Number of Lessons**	**Percentage**
Yes	4	27%
No	11	73%
	15	100%

- Hypothesis 4.

We present the behavior that occurred at the beginning and end of each virtual lesson in Table 28 and also the correspondence with H4.

Table 28: Heart rate behavior at the beginning and end of each lesson

Behavior of the Heart Rate in Each Lesson	**Slope Start**	**End**	**Correspondence with Hypothesis 4**
Decreases at the beginning and decreases faster at the end	-0.2088	-0.5779	No
Decreases at the beginning and increases at the end	-0.2096	0.5495	Yes
Decreases at the beginning and decreases faster at the end	-0.1698	-0.2714	No
Increases at the beginning and increases slower at the end	0.2757	0.1136	No
Increases at the beginning and decreases at the end	0.2085	-0.6794	No
Increases at the beginning and decreases at the end	0.8469	-0.8181	No
Decreases at the beginning and increases at the end	-0.1623	0.3963	Yes
Increases at the beginning and decreases at the end	0.1784	-0.2863	No
Decreases at the beginning and decreases faster at the end	-0.1795	-0.4427	No

Decreases at the beginning and decreases faster at the end	-0.1799	-0.9221	No
Increases at the beginning and decreases at the end	0.0139	-0.0167	No
Increases at the beginning and decreases at the end	0.0699	-1.5297	No
Decreases at the beginning and increases at the end	- 0.0914	0.9825	Yes
Increases at the beginning and increases slower at the end	1.4176	0.6167	No
Increases at the beginning and increases slower at the end	0.8603	0.1399	No

The heart rate decreased at the beginning and increased at the end in 20% of lessons; for that reason, we reject H4.

We analyzed each heart rate behavior presented at the beginning and the end of the lessons (Table 29). The percentage for each behavior is similar between them, so it is possible to conclude that there is no standard pattern. In another study [11], the researchers verified a standard heart rate behavior during various lessons. However, they evaluated it during lecture classes, and the students were physically present. In our study, the lessons were virtual, with different factors that could influence the participants' heart rate, like connection problems and the influence of external factors according to the place where they take the lessons that could affect their level of attention, etc.

Table 29: Behavior at the beginning and end of lessons

Heart Rate Behavior	Number of Lessons	Percentage
Decreases at the beginning and increases at the end	3	20%
Decreases at the beginning and decreases faster at the end	4	27%
Increases at the beginning and decreases at the end	5	33%
Increases at the beginning and increases slower at the end	3	20%
	15	100%

- Hypothesis 5.

In this hypothesis, we applied a process similar to H1, considering the activities before, during, and after passive learning activities, in this case, a video projection. We obtained four behaviors, which described the mean heart rate (MHR) before, during, and after a passive learning activity.

- Behavior one (high MHR-low MHR-high MHR): the behavior of the mean heart rate before and after the passive learning activity is higher than the behavior during this activity. It corresponds with H5.

- Behavior two (high MHR-low MHR-low MHR): the behavior of the mean heart rate before the passive learning activity is higher in comparison with the behavior during this activity, while the behavior of the mean heart rate after this activity is lower than the passive learning activity. It corresponds with H5.
- Behavior three (low MHR-high MHR-high MHR): the behavior of the mean heart rate before the passive learning activity is lower compared to the behavior during this activity, while the behavior of the mean heart rate after this activity is higher than that of this the passive learning activity. It is contrary to H5.
- Behavior four (low MHR-high MHR-low MHR): the behavior of the mean heart rate before and after the passive learning activity is lower than the behavior during this activity. It is contrary to H5.

However, this hypothesis focuses on the behavior before and during a passive learning activity since the first two behaviors represent a decrease and the last two an increase in heart rate during a passive learning activity. Table 30 summarizes the combination of these behaviors and their percentage.

Table 30: Correspondence with hypothesis 5

Behavior	Number of activities	Low/ High	Percentage	Correspondence with Hypothesis 5
Behavior one (high MHR-low MHR-high MHR)	2	5	45%	Yes
Behavior two (high MHR-low MHR-low MHR)	3			
Behavior three (low MHR-high MHR-high MHR)	1	6	55%	No
Behavior four (low MHR-high MHR-low MHR)	5			
	11	11	100%	

The increase in the heart rate could occur because, before each video, professors instructed their students to pay attention and to make an activity after the video projection, which could prevent students from entering a resting state during the video projection. These results allow us to rebuild H5 with this approach: if students are previously advised that they will have to develop an activity after a passive learning activity (such as a video projection), their heart rate could increase, and

consequently, so could their cognitive engagement. Overall, we partially accept H5 with the exposed approach.

We present a summary of the results of each hypothesis in Table 31.

Table 31: Hypothesis outcomes

Hypothesis	Results
Hypothesis 1 (H1)	We partially accepted H1, adapting the initial approach to the following: the mean heart rate has a significant variation with an active learning activity, indicating students experiment with cognitive engagement.
Hypothesis 2 (H2)	We partially accepted H2 with the following adaptation: The heart rate trend from the beginning to the end of the lesson depends on external and internal factors. The internal factors are linked with the active learning activities, mainly the duration and the moment in the lesson that the professor develops them.
Hypothesis 3 (H3)	The decrease in heart rate was biphasic, with a further decrease during the early stages of the lesson in only 27% of cases. For that reason, we rejected H3.
Hypothesis 4 (H4)	The heart rate decreased at the beginning and increased at the end in 20% of lessons; for that reason, we rejected H4.
Hypothesis 5 (H5)	We partially accepted H5 with the following adaptation: if students are previously advised that they will have to develop an activity after a passive learning activity (such as a video projection), their heart rate could increase, and consequently, so could their cognitive engagement.

3.4.3.3 Non-Self-Report Method vs. Self-Report Method

In this section, we constructed a quadrant model for relating the non-self-report method with the self-reported method. We analyzed two scenarios, the first related the mean responses of the questionnaire with the general heart rate variation (HRV). In this last variable, we took the data for the heart rate during whole lessons, that is, all activities. In the second scenario, we analyzed the same relationship of variables, but in the second variable, we only considered the HRV of active learning activities (ALA).

- First scenario: General heart rate variation vs. mean response of the questionnaire

In this analysis, we evaluated the 16 participants classifying them into four quadrants (Figure 25). Ten were located inside the quadrant I, one in quadrant II, one in quadrant III, and four in quadrant IV.

The classification of the 10 participants in quadrant I, indicates that they had a positive HRV, that is, an increase in the general mean heart rate (MHR) concerning the baseline. These students also reported a high cognitive engagement in questionnaires. This quadrant is the best scenery in this study because it proved that a positive HRV is related to high engagement.

One participant was in quadrant II; she/he had a positive HRV but reported a low level of engagement in the questionnaire. This result indicates that the student did not feel a high cognitive engagement during the whole lesson, but he could have moments or activities that caught their attention, increasing their heart rate. If a participant was in quadrant III, she/he had a negative HRV, and in the same way, the student reported a low level of engagement in the questionnaire.

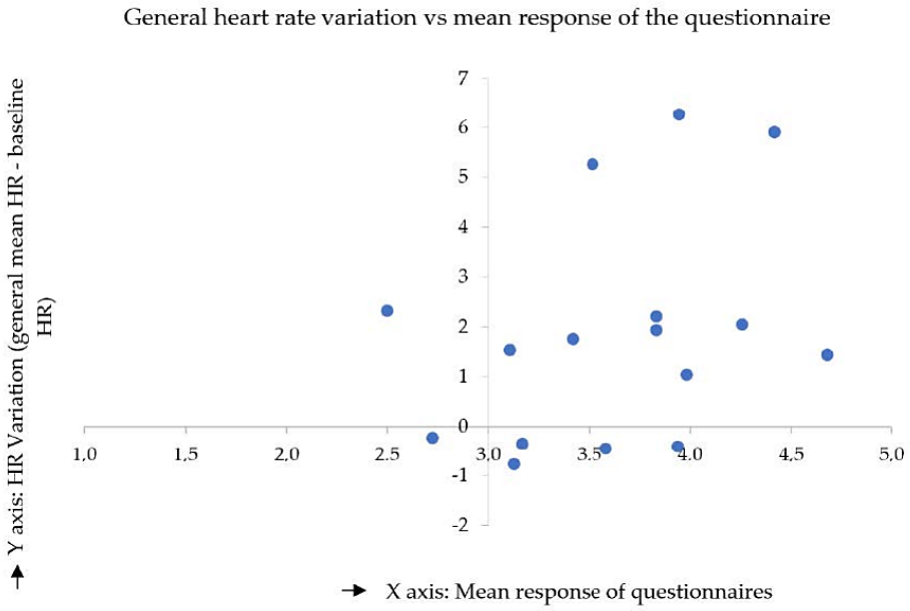


Figure 25: First scenario. General heart rate variation vs. questionnaire mean response

Finally, four participants were situated in quadrant IV; they reported a high engagement in the questionnaire. However, the general MHR decreased with respect to the baseline, a circumstance that may indicate that students were in an immersive state and not necessarily a low level of attention or a low level of cognitive engagement; this affirmation coincides with the results of the study made by Ronney et al. [97], who analyzed the behavior of the participant's heart rate while

watching a film; the results demonstrated that a drop in the heart rate might suggest an immersive environment followed by an increase in the attention paid to the film.

- Second scenario: Heart rate variation during active learning activities vs. questionnaire mean response.

In the same way, as in the first scenario, we evaluated the 16 participants with the difference that here we related the HRV during active learning activities (ALA) and the mean responses in the questionnaire (Figure 26).

Nine participants were in quadrant I, seven of them presented a positive HRV below three points when an ALA was developed. This behavior is similar to the first scenario, which indicates that ALA had a great influence on the behavior of a whole lesson. The quadrant I represents that participants were making a mental effort to acquire a high level of attention, a circumstance that resulted in a positive variation of the heart rate. The other two participants had a positive HRV greater than three points. This quadrant represents the best scenario; with these results, we can affirm that a positive HRV is linked to high cognitive engagement.

Two participants were in quadrant II, unlike the first scenario where we found one participant in quadrant II and the other participant in quadrant III. This behavior indicates that, although the participant in quadrant III reported a low cognitive engagement in the questionnaire, the ALA developed by the professor caught her/his attention, which meant an increase in the HRV and caused her/him to be in the quadrant II in the second scenario.

Five participants were in quadrant IV. As we explained, this quadrant represents an immersive state of the participants. The participant who was in quadrant I in the first scenario is now in quadrant IV in the second scenario. This change means that she/he was in an immersive state when the professor carried out ALA. On the other hand, one of the participants had a significant negative HRV, below eight points, which indicates that her/his concentration was higher during ALA.

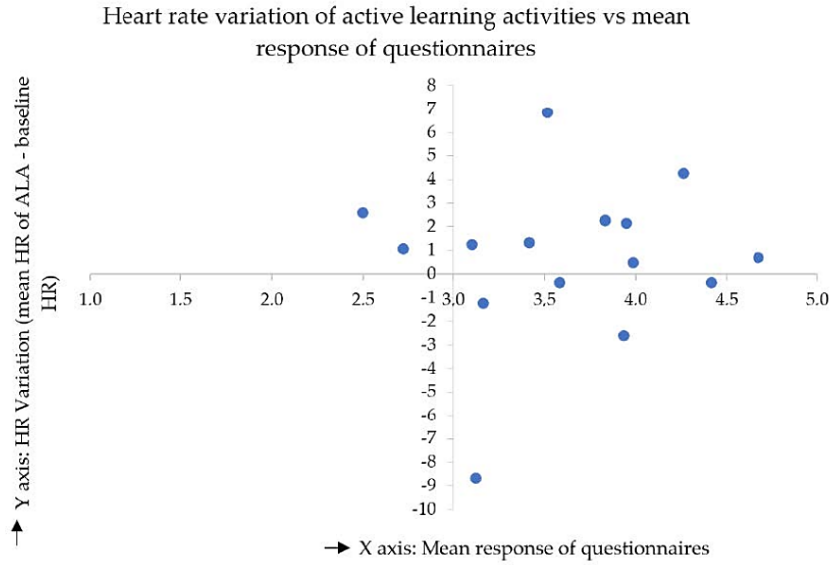


Figure 26: Second scenario. Heart rate variation during active learning activities vs. questionnaires mean response

Overall, with the analysis performed and illustrated in the first and second scenarios, the study shows that although there were heart rate variations (causing location changes for some participants inside the quadrant), the number of subjects for each quadrant is similar. This condition allows us to suggest that ALA developed by professors determines the behavior of the MHR throughout the whole lessons.

Using the quadrant analysis, it was possible to ascertain that combining a non-self-report method (heart rate) with a self-report method (questionnaire) is advantageous for measuring cognitive student engagement since the comparison of the heart rate against the report given by each participant provides more information about the influence of ALA on the heart rate.

3.5 Discussion

In this study, we conducted an exploratory research implementing a non-self-report method to measure the cognitive student engagement using a physiological characteristic, the heart rate. We have measured and analyzed this variable, using a heart rate band, in 16 participants from the Industrial Engineering program, at a Colombian University located in Bogota. With the collected data, we evaluated five hypotheses. Below, we will present and discuss the results of each hypothesis.

- Hypothesis 1.

To analyze H1, we evaluated the heart rate behavior before, during, and after an active learning activity (ALA); we found that 41.4% of data corresponded with H1. Since ALA was an important matter in this study, we applied an ANOVA test to evaluate the heart rate during an ALA against each participant's baseline, an analysis that demonstrated a statistically significant difference between these variables. We partially accepted H1, adapting the approach to the following: the mean heart rate has a significant variation with an active learning activity, indicating students experiment with cognitive engagement.

In comparison with similar activities developed in a face-to-face environment, the heart rate had a variation if the student was exposed to active learning activities; however, in the study performed by Darnell and Krieg [11], the heart rate had a significant uptick, while in our study, in virtual lessons, the heart rate had a significant variation that could be positive or negative. With this perspective, we could deduce that one of the main factors that affect the student engagement is the environment and not the activity that is developed. For that reason, we conclude that it is valuable to design activities that consider the learning environment to capture the student's attention and improve her/his knowledge.

- Hypothesis 2.

We evaluated H2 with the heart rate trend; if it was negative indicated a decrease and if it was positive indicated an increase in the heart rate from the beginning to the end of the lesson. From a total of 15 lessons, 60% presented the behavior expected by H2. For these results, we partially accept H2 with the following adaptation: the trend of the heart rate from the beginning to the end of the lesson depends on external and internal factors, the internal factors are linked with the active learning activities, especially the duration and the moment in the lesson that the professor develops them.

In the study of Darnell and Krieg [11], the heart rate had a decreasing trend in the morning lessons; they found that this behavior was caused mainly by external factors such as mental fatigue and the accumulation of multiple classes, among other reasons. We found that these aspects happened in virtual lessons, but internal factors also affected the trend. These factors are linked with the active learning activities that professors can plan and monitor during each lesson.

- Hypothesis 3.

H3 had a strong dependence on H2, because H3 requires the trend during a lesson to decrease. After evaluating the 15 lessons, we found that only 27% of them had the behavior expected in H3, and for this result, we rejected H3.

The biphasic shift with a faster decline in the first minutes and a slower decline in the remainder of the class was not confirmed in the study developed in the United States [11]; we did not find the biphasic behavior described in the development of virtual lessons.

- Hypothesis 4.

After analyzing the behavior of the heart rate at the beginning and the end of each lesson, we found that only 20% of the lessons achieved H4. After the analysis, we concluded that there is no standard pattern related to this hypothesis, and for this reason, we rejected H4.

The behavior at the beginning and the end of the lesson in the study of Darnell and Krieg [11] showed a drop at the first three minutes and an uptick in the last three minutes of the lesson; for this reason, they excluded these three minutes for the analysis of the others hypothesis. They determined that this behavior could happen for external factors related to a face-to-face environment, such as arriving in a classroom and speaking with other students or thinking about the next class or next activities after finishing each lesson. In our study, we did not find a notable change at the beginning and the end of each virtual lesson; we consider these data for other analyses.

- Hypothesis 5.

We analyzed 11 passive learning activities and found that 45% of them presented the behavior described in H5. All activities were a video projection; however, before students watched the video, the professor indicated to them that there would be an activity after the video, a factor that could influence the results. We partially accepted H5 with the following adaptation: if students are previously advised that they will have to develop an activity after a passive learning activity (such as a video projection), their heart rate could increase, and consequently, so could their cognitive engagement.

The study performed on students of medicine in the United States [11] found that during a short video projection, the heart rate appears to decrease greatly since

it is categorized as a passive activity, the difference with our study consisted in the instruction that the professor gave to students, which was developed a task after a video projection, a condition that modified the behavior of the heart rate. In addition to analyzing the hypotheses, we made the relationship between the quantitative data vs. qualitative data from the questionnaire.

3.5.1 Non-Self-Report Method vs. Self-Report Method

We related the heart rate variation (HRV) of whole lessons and the HRV during the active learning activities (ALA) against the response that participants gave in the questionnaire; the VHR refers to the difference between mean heart rate and the baseline, we explored the behavior of the 16 participants.

We used a quadrant model (Figure 25 and Figure 26); two quadrants stood out over the others; Quadrant I reflected that the HRV was positive, and the responses in the questionnaire indicated a high level of cognitive engagement, the majority of data was located in this quadrant; the first stage, HRV of whole lessons, had 10 participants, and the second stage, HRV during ALA, had nine participants. Quadrant IV was the second predominant one. It represented an HRV negative, but the questionnaire's response indicated a high level of cognitive engagement; this situation reflected that participants could be in an immersive state during the ALA, and not necessarily a low level of engagement. Finally, the results suggest the behavior of the heart rate during a whole lesson might be determined by the ALA that professors developed in each lesson.

3.5.2 Limitations, Recommendations, and Future Research

We used the heart rate as a tool for measuring student engagement in virtual lessons during the COVID-19 pandemic, and we had limitations regarding the difficulty of eliminating environmental and external influences generated by the inconveniences of having access to resources and tools necessary for the development of the lessons, such as internet connection problems, unstable electricity, lack of an appropriate space without interruptions, a computer without the required capacity to run several programs and software at the same time (lesson connection software and programs to develop activities during class), and inconvenience with the phone that collected heart rate data (the reason for removing some data from the study). These limitations affected the level of attention of the participants and sometimes caused them to carry out other activities in parallel to the lessons. The difficulty of eliminating environmental and external influences is a known limitation in the use

of heart rate as a tool for identifying engagement; for this reason, for future research, we recommend using the heart rate as a non-self-report method in combination with a self-report method such as a questionnaire that allows the identification of external factors that could affect the participant's attention in addition to the perception that she/he had of the lesson and the activities developed.

Another alternative we recommend to reduce the influence of external factors is to use supplementary biometric measures that allow us to identify additional characteristics that affect the heart rate, like emotions, motivation or level of concentration, factors that strongly influence student engagement. The supplementary biometric measures we suggest are: the detection of facial expression, breath rate, skin temperature, and conductance or brain signals.

In this study, we made an exploratory investigation limited to the number of participants, the quantity of heart rate bands, and a specific lesson theme (human talent management). The sample number of participants was between the ranges of other studies in the sector; however, we recommend that for future studies, the researchers increase the sample and evaluate student engagement in other engineering subjects. We hope our study can serve as the basis and input for future research related to the analysis of cognitive student engagement using heart rate as a non-self-report method.

Using the heart rate to analyze student engagement has the advantage of data being collected in real-time. However, the data processing and the analysis require additional time. This limitation means that teachers do not receive feedback in real-time to make the necessary decisions to modify or adapt the methodology of the course. For this reason, a future challenge could be the development of a model that processes and evaluates the heart rate data in a shorter time or even in real-time, which can be used by all students in a lesson and provide feedback to the professor.

The heart rate is a physiological parameter used mainly by enterprises to evaluate customer behavior. Carrying out this study, we aim to demonstrate that heart rate analysis is an effective tool that can determine cognitive student engagement. We expect this study could be a base for future research looking to deepen the evaluation of the variables that influence heart rate in an academic environment.

3.6 Conclusions

Student engagement allows educational institutions to improve their decisions regarding methodologies, evaluation of quality, and feedback. The methods to determine student engagement are divided into self-report methods, such as questionnaires, surveys, and analysis of these, and non-self-report methods, which use physiological characteristics such as heart rate, brain signals, analysis of facial expressions, etc. In Colombia, the investigations only used self-report methods.

In this study, we develop an exploratory investigation to determine the level of student cognitive engagement through heart rate, during the development of active learning activities. We used heart rate bands and a mobile application to collect the data from a sample of 16 students taking the Human Talent Management course of the industrial engineering program of a higher education institution in Bogota, Colombia.

The results confirm that heart rate can be used as a tool for measuring cognitive student engagement in distance learning, especially if the professor develops an active learning activity since, statistically, the heart rate has a significant variation with respect to the baseline heart rate during the development of these activities. At this point, it is important to clarify that this difference could be positive or negative. A positive variation implies an increase in the heart rate because the study subject is making a mental effort, and a negative variation means an immersive state, i.e., the active learning activity captured the student's attention and immersed her/him in this environment, causing her/him to isolate herself/himself from any other activity. In the development of virtual lessons, one of the main concerns of the professors is to identify activities that encourage the participation of students, capture their attention, and allow the transmission of knowledge. In this study, we found that active learning activities achieve these objectives because spaces are generated within the lessons that allow students to concentrate on the activities developed, resolve doubts and connect their past experiences with new knowledge.

Using a quadrant model, we confirmed that combining a non-self-report method and a self-report method allows us to analyze engagement from a broader perspective. This association allows us to relate the engagement reported by the students with the results obtained from the physiological characteristic. In our study, one of the results suggested that, during an active learning activity, most participants reported a high level of cognitive engagement, and the heart rate variation had a significant difference with respect to the baseline, a result that was

evident in the ANOVA. However, in this analysis, it was possible to identify that this difference could be positive or negative.

In the development of this research, we found that students feel more comfortable, feel less pressure, and are more willing to participate in a study if factors such as student engagement are measured using a non-self-report method because they sent us the heart rate data immediately after the end of the lesson without having to remind them to send the data. However, the opposite happened with the self-report method because we had to ask them to fill out each questionnaire at least twice and sometimes up to four times. The above shows that students are interested in participating in non-self-report methods and the importance of rethinking how self-report methods are implemented.

We confirm that the heart trend from the beginning to the end of the lesson depends on external and internal factors. The external factors include instability in the internet connection and activities that students may be developing in parallel to lessons, and the internal factors, which professors can control, are linked with the active learning activities. The internal and external factors presented in a face-to-face lesson are very different from those presented in a virtual lesson. In a face-to-face lesson, the external factors that affect the concentration of students are reduced due to the learning environment that a classroom provides. However, the external factors are greater and more variable in a remote environment. For this reason, the active learning activities that professors develop become more relevant, especially in terms of the duration and time of the lesson in which they are performed. These activities provide a balance at the beginning, middle, and end of the lesson.

Concerning passive learning activities, if students are previously advised that they will have to develop a task after a passive learning activity (such as a video projection), their heart rate could increase, and consequently, so could their cognitive engagement. The instructions for the activities to be carried out after the video projection was focused on the topic that the students were learning and generated a discussion between the work groups or between the students and the professor. This particularity should be considered if professors want to implement a passive learning activity to promote cognitive engagement.

We find that heart rate did not present a pattern in the biphasic analysis or a pattern of behavior at the lesson's beginning and end. The four heart rate behaviors found at the beginning and at the end of the lesson allow us to deduce that the

variation depends on external factors that may occur before and after the class and that the professor cannot control; for example, other academic activities of different courses or personal activities that can cause a variation in heart rate.

We expect that this study can provide input for future research assessing student cognitive engagement in higher education and motivate researchers to use physiological characteristics as a measurement tool.

The results of this investigation have been published and can be consulted at https://doi.org/10.3390/educsci11090540 [22].

Chapter 4

User Engagement Comparison Between Advergames and Traditional Advertising Using EEG: Does the User's Engagement influence Purchase Intention?

In Human-Computer Interaction (HCI) context, understanding UE while interacting with a product or service can provide valuable information for enhancing the design process. UE has been a priority research theme within HCI, as it assesses the user experience by studying the individual's behavioral response to some stimulus. Many studies looking to quantify the UE are available; however, most use self-report methods that rely only on participants' answers. This study aims to explore a non-traditional method, specifically EEG, to analyze users' engagement while interacting with an advergame, an interactive form of advertising in video games. This study aims to understand if a more interactive type of advertising will enhance the UE and whether, at the same time, it would influence the user's purchase intention (UPI). To do this, UE was computed and compared during the interaction with an Advergame and a conventional TV commercial while measuring the participants' brain activity. After the interaction with both types of advertising, the UPI was also evaluated. The findings demonstrate that a more interactive advertisement increased the participants' UE and that, in most cases, a UE increment positively influenced the UPI. This study shows an example of the potential of physiological feedback applications to explore the users' perceptions during and after the human-product interaction.

4.1 Introduction

With an increasing number of digital services, HCI studies regarding the analysis of interfaces and approaches to exchange information are a must. In particular, exploring innovative techniques that allow researchers and practitioners to understand users' needs without bias may foster HCI applications in promising consumer-content interaction fields. Affective computing developments have been a matter of interest for interdisciplinary fields due to the practical implications concerning the study and design of systems capable of recognizing and interpreting human emotions. The marketing and video games industry are no exception. Some years ago, video games were a minor activity exclusively earmarked for kids, leaving aside the adult audience. The actual situation of video games is undoubtedly much more different; video games ranked first in leisure activities, getting over the traditional ones, like cinema and music [257]. Additionally, its importance continues to increase, reaching a media resonance and social impact due to the development and implementation of new technologies, especially in an era affected by the pandemic of COVID-19, where technology has taken a significant role in the entertainment market in terms of popularity and profitability. The impact of the ongoing pandemic, social restrictions, and the recommendation to stay at home have significantly contributed to a rise in the gaming industry's numbers of users.

In an environment where consumers have the choice to pay and get what they desire, advertising can be quickly rejected; the impact of video games has not gone unnoticed by the publicity market, a sector reinventing itself to find new ways to reach an even more demanding audience. The advergames, a hybrid between advertising and entertainment content in video games, can contribute to a better perception of advertising by developing new possibilities for marketing communication. Advergames have also gained a competitive advantage [258] for attracting and engaging users due to their interactivity and high exposure to a brand or product [259] while offering a non-intrusive experience. The user is the one who addresses the game and interacts with it voluntarily. Also, this type of interactive advertising allows easy customization since the brand can include its style and values to create a unique and representative product, thus contributing to the brand personality and attracting more users who feel identified with the brand.

This effectiveness is achievable thanks to the capacity of introducing advertising content inside an environment where the users have shown a good perception of the publicity. Furthermore, the value of Advergames lies in their ability to provide a compelling advertising message that consumers are more

willing to accept [260]. Due to these advantages and the significant impact that video games have worldwide, advertising campaigns should consider Advergames, a non-saturated leisure platform [261], as an opportunity to increase UE and contribute to the user purchase intention (UPI). In other words, the Advergames could take advantage of the UE with video games to reach a more demanding audience and increase the willingness to acquire a product.

UE, a typical human-computer interaction parameter, has been described as the degree of focus and immersion in a particular task [262]. Traditionally, this indicator has been measured using almost exclusively self-report measures; however, in order not to rely only on respondents' answers, technological advances have made possible the use of new tools that can provide physiological outputs to examine the "ground truth" of the users' perceptions. Among these EEG, which is becoming a potential tool for exploring UE. Indeed, by analyzing the EEG data collected while participants were exposed to a stimulus, McMahan and Freeman's studies [12], [99] have demonstrated that EEG-based metrics can be used to determine whether a user is more or less engaged. The results from the literature would suppose that an advergame will provoke higher Engagement than a TV commercial since TV is a passive media; however, it is unclear if a more interactive type of advertising would lead to a higher purchase intention. The goal of meaningfully quantifying the UE using physiological tools such as EEG will provide additional helpful information that, combined with traditional methods, can enrich this research field.

This empirical study aims to validate if a more engaging type of advertising would consequently increase the users' purchase intention. To do this, we have created an experiment where the users are exposed to two advertisements for the same product whilst their brains' activity is being recorded. In this way, we aim to compare a traditional advertising campaign with an advergame to quantify the UE difference using EEG. A validated questionnaire will be used to determine the purchase intention before and after the experiment.

This chapter is structured as follows: Section 4.2 presents the research background, including a review of the UE in video games, the EEG as a method for understanding the UE, and the conceptual relation between UE and purchase intention. Section 4.3 sets the methodology, the experimental setup, and the data

analysis. Section 4.4 presents the analysis results, and sections 4.5 and 4.6 contain discussion and conclusions.

4.2 Research Background

UE has been a matter of interest in different fields, including education, healthcare, and entertainment. The way UE has been evaluated differs from study to study; for the purpose of this research, we will focus our attention on the most common methods to measure the UE during videogames interactions and the exploration of EEG as a means to measure this indicator.

4.2.1 An overview of User Engagement in Video games

UE can be defined as the absorption level and willingness to execute a task [262]. In a recent study, Kniestedt et al. [263] delineated the Engagement definition in applied games as a concept involving the state of concentrating attention on a task and the involvement with the context where that task occurs. The UE in videogames has been a matter of interest in different studies [21], [264]–[268] under the idea that users can be engaged in activities through meaningful interactions. The interactive possibilities that video game technologies offer can enhance Engagement more than other activities. Brockmyer et al. [21] designed the Game Engagement Questionnaire (GEQ) focused on analyzing video games' violence; the study explores the Engagement experience in four dimensions, absorption, flow, presence, and immersion. It concludes that it is possible to identify the users' psychological Engagement when playing video games and that a higher UE can significantly impact game playing.

On the other hand, Bianchi-Berthouze [266] considered how body movement could affect the UE during gameplay. The movement-based engagement model specifies the relationship between movements and Engagement. The model classifies the body movements into five groups and describes their relationships with the Engagement. The study concludes that the freedom offered by video games plays an essential role in the UE, allowing a more in-depth immersion in the scenarios presented, attracting users to continue exploring and engaging more and more with the game. This work has been widely appreciated by the scientific community and is an excellent example of the importance of physiological measurements to better understand the UE.

Another significant study is the one carried out by Martey et al. [267], who measured the UE with video games, measuring different characteristics that may influence the users' perception. These characteristics are a player avatar, visual realism, and narrative. In this study, the authors measured five indicators (a self-report survey, the attention to the stimulus, Galvanic skin response (GSR), mouse movements, and game click logs) when playing a video game to measure how these characteristics can influence the capacity of a video game to engage the user. The results indicated that physiological measurements (GSR, mouse movement, and clicks) are highly related to users' expressions and feelings and can provide reliable information for UE identification and analysis.

Abdul Jabbar and Felicia [268] developed a model where emotions and thoughts play an essential role in UE and Learning. The study illustrated the impact of some gaming features on cognitive and emotional levels by classifying the engaging elements into four types: motivational, interactive, fun, and multimedia. The study found that some elements that might influence the UE in the gameplay are related to visuals, role-play, obstacles, virtual environments, control/choice, and rewards.

Likewise, O'Brien and Toms [19] created a survey to test the UE of software applications named the User Engagement Scale (UES). In this survey, users are asked to answer questions about their experience with the product. This survey was later adapted by Landa-Avila and Cruz [269] for a virtual game to analyze six aspects: Perceived Usability, Aesthetics, Novelty, Felt Involvement, Focused Attention, and Endurability. After data analysis, the authors found that the UES questionnaire can be used to measure the UE in videogames context; however, there were objections about the test's duration and misunderstandings about some items. This situation was later examined by O'Brien et al. [270], who proposed the UES short form.

Other studies on UE analysis in videogames are listed in Table 32. Most of these studies, however, relied only on self-report methods, such as questionnaires, interviews, surveys, and scales, in which participants are asked to answer questions or provide responses to prompts that are designed to collect data on a particular topic or construct. The data collected through self-reported methods can be subjective and may be influenced by various factors, such as the participants' memory, motivation, and willingness to reveal personal information. Despite these

limitations, self-reports have been widely used as a method for UE analysis, and as a consequence, this could lead to biased outcomes due to the nature of the responses. In this sense, self-reports could be compared and enhanced with other experimental approaches that do not depend entirely on participants' responses, such as the case of EEG.

Table 32: UE analysis in videogames

Author	Method	Purpose/Outcome
Mayes and Cotton [271]	Questionnaire	Development of an Engagement Questionnaire (EQ) in video games
Lankoski [272]	Framework	Engagement definition classified as goal-related or empathic.
Schønau-Fog [273]	Survey	Definition of a Player Engagement Framework based on Objectives, Activities, Accomplish, and Affect.
Schønau-Fog and Bjorner [274]	Interview	Method to classify the experience of Engagement with video games into six types: Intellectual, Physical, Sensory, Narrative, Social, and Emotional Engagement.
Corem et al. [275]	Scale	Proposal of a player-matching system based on the Elo rating system.
Sharek and Wiebe [276]	Physiological (haptic) & Survey	Measure of Engagement based on how many times a participant clicked a game-clock during gameplay.
Wiebe et al. [277]	Scale	A modified version of the User Engagement Scale (UES) for video game research.
Kirschner and Williams [278]	Interview	Gameplay review method (GRM) for players' Engagement using interviews and audiovisual recordings
Pope et al. [13]	Physiological (EEG)	EEG engagement index based on Electroencephalographic signals.
McMahan et al. [12]	Physiological (EEG)	Identification and verification of the EEG engagement index developed by Pope et al. [27] as a valid indicator of UE with video games.
Phan et al. [46]	Scale	Game User Experience Satisfaction Scale (GUESS)
Sreejesh and Anusree [279]	Survey	Study on the effects of cognition demand and brand attention.
Sawyer et al. [280]	Scale	Hierarchical Bayesian method to model player engagement.
Nermend and Duda [281]	Physiological (eye tracking, GSR) & Questionnaire	Methodology for choosing the location of advertising in games, using eye tracker and GSR.
Barclay and Bowers [282]	Survey	Use of the Revised Game Engagement Model (R-GEM) to conclude that immersion in an activity may not only be a result of highly usable systems or particularly receptive users but an effect of the experience itself.

4.2.2 EEG as a means for understanding the Engagement

The literature on the methods, measures, and elements that influence the UE with videogames shows a predominance of self-report methods; however, methods

based on physiological analysis are becoming more accessible due to the technological advances that have increased the availability and usability of these systems. An example is a study conducted by McMahan et al. [12]; in this research, the authors used EEG to evaluate the player task engagement in videogames in two situations, during normal gameplay and player death. The study identified that the Engagement corresponds to immersion states, concluding that higher levels of Engagement are present during death events compared to general play. Likewise, a recent study [283] used an educational videogame created to test medical students' clinical skills and track their Engagement using EEG. The results showed a correspondence between the EEG outcomes and the participants' performance.

The evaluation of Engagement with EEG has also been explored in the education field; Chaouachi and Frasson [98] analyzed the effect of Engagement on the students and found that it strongly influences the response time and can be an indicator of learners' performance. At the same time, the authors used the Engagement index, initially proposed by Pope et al. [13] and later validated by Freeman et al. [99]. Similarly, Coelli et al. [284] evaluated the relationship between the level of cognitive engagement and focused attention, concluding that EEG can be used to detect changes in mental state and subjects' reaction times. A recent study [285] proposed a device prototype consisting of an EEG headset and a scarf that provide haptic feedback when a decrease in attention is detected.

Considering the emotional research, Ramirez et al. [286] conducted a study based on EEG to analyze the emotional effect of music in advanced cancer patients; their findings showed a decrease in anxiety and tiredness. Likewise, in a previous study, Giraldo and Ramirez [287] described an approach to calculate arousal and valence values from EEG activity in real-time. On the other hand, Ramirez and Vamvakousis et al. [288] explored a machine learning approach to detect emotions from EEG signals. In these studies, the authors computed and validated EEG-Based indices for obtaining information about the users' emotional states.

A further study [289] explored the Engagement analysis with advertising; this study focused on traditional advertising and did not use a validated Engagement EEG index; the EEG data were globally recorded and then correlated with the participant's answers to a questionnaire. However, the results were not conclusive, and the authors recognized the need for more profound research in this field. Likewise, other studies [290] have focused their interest on analyzing players'

emotions in VR gaming using EEG data and comparing their results with self-report methods.

The studies on Engagement and EEG showed that EEG-based metrics are suitable for studying UE. However, despite the advances in the study of Engagement in advertising and videogames, these two fields have been explored individually; consequently, there is a research gap regarding the Engagement during Advergames interactions using EEG.

4.2.3 Relation between Engagement and User Purchase Intention in Advergames

UPI can be defined as the conscious decision of a user to buy a particular product [291]. This degree of willingness to pay is a variable that depends on several factors, for example, the product perception, the attitude toward a specific purchase, the interaction experience, the Engagement with a particular product or brand, and the customer service. Survey instruments have been a common choice for assessing these variables and ultimately estimating the UPI.

Goh and Ping [264] developed and validated a post-game questionnaire to measure the purchase intention and attitude toward the Advergame experience, the brand, and ads in general. The study concluded that the attitude toward the brand positively influences the UPI and confirms the advergames' added value in effectively increasing the UPI of the advertised product.

Chen [292] developed a model of the in-game factors influencing the user purchase reaction with an Advergame. The study identified that audiences are more likely to develop a purchase intention and positive brand attitudes when they are engaged and attracted during the Advergames. On the other hand, Catalan et al. [293] identified a group of elements that could affect user experience and purchase reaction in a mobile advergame. The study defined the following factors that might influence the UPI: skills, challenge, interactivity, focused attention (Engagement), and telepresence.

Other studies concluded that advergames lead to a higher purchase desire than tv commercials [294], also that UPI and attitude towards a brand increase when there are elements of interactivity [295], and that children who are more involved and have a positive attitude during the game show a higher UPI [296].

Finally, Chang et al. [297] proposed a conceptual framework for exploring the congruity, integration, and prominence as variables persuading the interest and purchase intention during in-game advertising. The study suggested a survey instrument for measuring the UPI and concluded that user attention/engagement positively affects purchase intention during gameplay.

Considering the previous findings that highlighted UE as one of the most significant variables that could influence the UPI, in this research, the UE influence on the UPI during an advergame interaction and projection of a tv commercial has also been analyzed.

4.3 Methods and Tools

The relationship between videogames and advertising is complex and multifaceted, with each industry influencing and benefiting from the other in various ways; in the intersection between there are the advergames (Figure 1), which provide a unique and highly engaging platform for advertisers to reach consumers, with in-game ads and sponsored content offering new and innovative ways for brands to connect with their audience and promote a product or service through the use of interactive and engaging gameplay. This strategy relies on user engagement to be successful, with the level of engagement (UE) influencing the effectiveness of the advertising and the likelihood of a user making a purchase (UPI). The interaction between these three contexts (videogames, advertising, and advergames) and the UE influence on the UPI frames this research. (Figure 27).

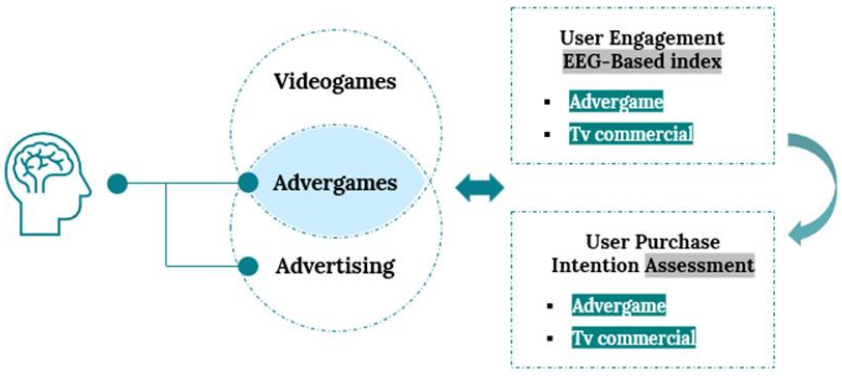


Figure 27: Model of UE influence on UPI

This research aims to measure the UE with an Advergame and a traditional advertising campaign to analyze if the UE has an incidence on the UPI of a product or brand exposed. To achieve this, we focused the literature background analysis on previous UE and video games research, EEG as a method for UE identification, and the UE influence on the UPI in advergames.

The literature review shows that no study on advergames has been conducted using EEG as a method to measure the UE and its influence on the UPI. Besides, we want to contribute to this field by endorsing previously validated tools employed individually in related areas (games and advertising) to verify the hypothesis: "*A more interactive type of advertising impacts the user perception and engagement, positively influencing the purchase intention*."

To verify the previous hypothesis, the participants' physiological reactions are measured using EEG to analyze the UE during an advergame and a tv commercial. After both advertising interactions, the UPI is calculated using a questioning assessment.

4.3.1 EEG Engagement Index Data Analysis and Feature extraction

The neuronal electrical activity is composed of different frequencies that can be obtained through the EEG signal; these brain waves are grouped into frequencies bands: Theta (θ), Alfa (α), Beta (β), and Gamma (γ). Theta waves have a frequency of 4-8 Hz, Alpha 8-12 Hz, Beta 12-25 Hz, and Gamma 25-45 Hz. These frequency bands are commonly associated with diverse cognitive processes [98].

Beta (β) power is related to system activation and higher mental activity of the brain when a person is aware and cognitively engaged. In contrast, alpha (α) is associated with lower mental vigilance and usually appears in sleep-wake cycles; at the same time, theta (θ) activity occurs most often in sleep or deep meditative states. Pope et al. [13] proposed an EEG-based index to analyze the UE; in their research, the authors assessed three possible indices computed using the EEG frequencies bandwidth and suggested the most accurate UE index (Equation 2):

$$Engagement\ Index = \frac{Beta\ (\beta)}{Alpha\ (\alpha) + Theta\ (\theta)} \tag{2}$$

Following this approach, the UE index (Equation 2) considers the ratio between the beta waves (higher mental activity of the brain) and the sum of the theta and alpha waves (both related to lower mental activity of the brain).

This study was carried out using a mobile EEG headset (Emotiv EPOC+) composed of 14 saline-based electrodes (AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2) located according to the international 10-20 sensor placement system (Figure 28) [298]. Two additional CMS/DRL reference channels are located at P3 and P4. The sampling rate was 128 Hz, and the bandwidth was between 0.2 – 45 Hz. The band power calculation is performed at 0.125-second intervals (8Hz). We applied a Fast Fourier Transformation (FFT) to the most recent 2-second epoch of EEG data and averaged the FFT squared magnitude across the frequencies in each band. Before performing the calculation, the EEG stream passes through a 0.18Hz high-pass FIR filter; to improve the accuracy of the spectral analysis and reduce artifacts from the procedure a Hanning window was implemented. For the engagement assessment, Equation 2 was employed. Each participant's Engagement index was calculated using the averaged measurement from all sensors.

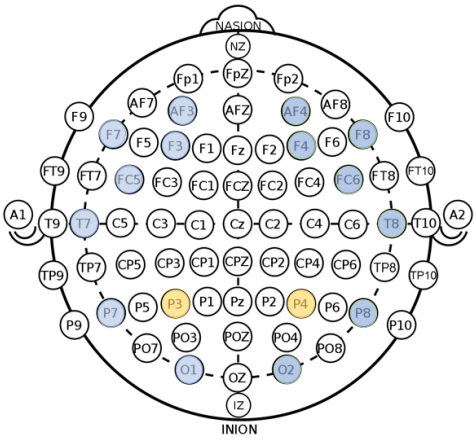


Figure 28: Sensor location. The electrodes' positions employed in this study are highlighted

Considering that in physiological studies, the initial baseline and the subsequent responses (after stimulus) are highly individual-dependent and differ from participant to participant, there are no absolute (max or min) values for UE. To help reduce errors associated with individual differences, this research employed a "within-subject design" experiment, often used in similar studies [12], [98], [99], [299], to regulate the subjects' measurements by exposing them to all experimental conditions. Users bring their own background and current physical and mental state to the test. So, in order to minimize the random noise, the EEG data is separated into two phases; the first contains the baseline recording during a relaxed period, useful to identify the primary user’s state, and used as a reference point for comparing the brain’s activity during different tasks. The second contains the

electrical brain data while exposed to a stimulus, in this case, while interacting with the Advergame and while watching the traditional advertising. By analyzing and contrasting the brain activity difference between the baseline and the activated engagement during the stimuli, it is possible to identify the activated response and, thus, the increment/decrement of the engagement index; if it increases, a higher UE is expected (Figure 29).

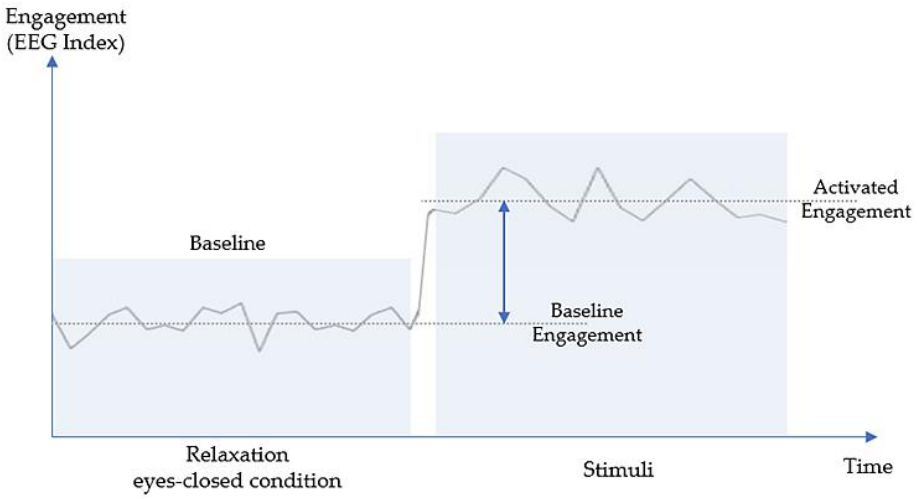


Figure 29: Engagement Baseline vs Stimuli activation

In this way, the participants in a within-subjects design serve as their own control by providing baseline metrics across the different stimuli. After analyzing and normalizing the entire signals, it is possible to generate a general comparable data analysis for all the participants exposed to the same experiment. The goal is to measure the variation resulting from the different stimuli for the engagement outcomes.

4.3.2 Experiment Setup

Our study consisted of a controlled experiment (Figure 30) conducted in a laboratory setting with 24 healthy participants, 13 women (55%) and 11 men (45%), aged between 23 to 45, recruited in person. All of them reported computer skills. All participants signed an informed consent after being briefed about the experiment, the use of their data, and its protection. Each user was accompanied to perform the test in a controlled environment, a closed room equipped with an adjustable chair, a 40-inch display monitor, and a gamepad planned to avoid situations that may influence the results.

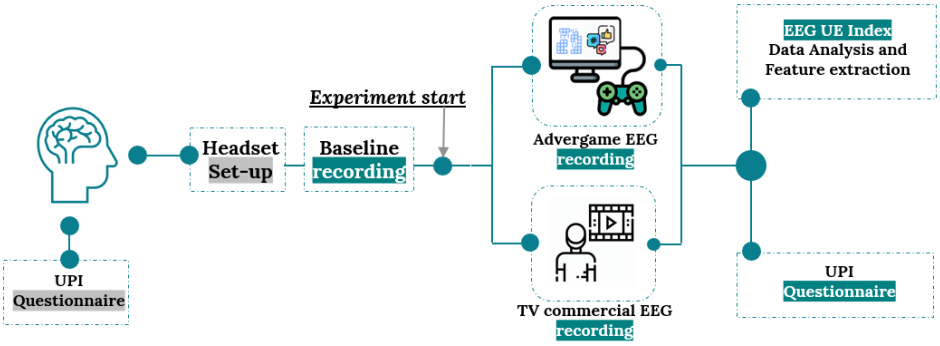


Figure 30: Experiment Setup

First, the users were requested to fill in the purchase intention questionnaire according to the original perception of the product selected for the study. The EEG headset was positioned on the participant's head, and the correct connection of the electrodes was verified. The participant is invited to relax for 3 minutes. After the training phase and setting up, to facilitate the immersion and successfully conduct the experiment, the lights were turned off.

A baseline period of 30 seconds was recorded during eyes-closed condition. Half of the participants were randomly assigned first to play an Advergame and then proceed with a TV commercial, while the other half initially watched the TV commercial and then continued with the Advergame activity. In both cases, the participants were asked to play the Advergame for 4 minutes and exposed to a TV commercial for 3 minutes while measuring their brain activity. Between one activity and the other, the participants were invited to relax for 2 minutes. At the end of each type of advertising, the participants were requested to fill in the purchase intention questionnaire again.

To evaluate the UPI, we used the purchase intention evaluation proposed by Chang et al. [297] to assess the consideration, desire, plan, and likelihood of buying the advertised product using a seven-point Likert scale.

The selected product belongs to a well-known brand of carbonated soft drinks. The TV commercial displays an urban scenario with young people singing and dancing in the street while inviting the spectators to join their march, the melody set in the background recalls the brand's iconic music. The Advergame is an endless runner third-person perspective game developed to avoid obstacles by running,

dashing, and jumping; the user's role is to save dehydrated people by collecting and delivering them cans of drink. The atmosphere is designed to show branded ads blended with the surroundings throughout the game.

4.4 Results

The raw EEG data was collected and processed. Artifacts due to body movements and signal noise were removed. Twenty results from the total sample were deemed suitable for the objectives of this study. The EEG data were segmented into the baseline (closed-eyes condition) and activity period when interacting with the Advergame or watching the tv commercial. In order to determine and contrast the EEG engagement index between periods, the baseline data were compared to the post-stimulus response for both the Advergame and the tv commercial; this way, it was possible to examine the influence of the advertising on the UE.

The EEG engagement index average for each one of the participants is shown in Figure 31, divided into the baseline and activity periods. The results show that during the Advergame interaction, the Engagement was always higher than the baseline period, indicating increased attention and vigilance while gaming.

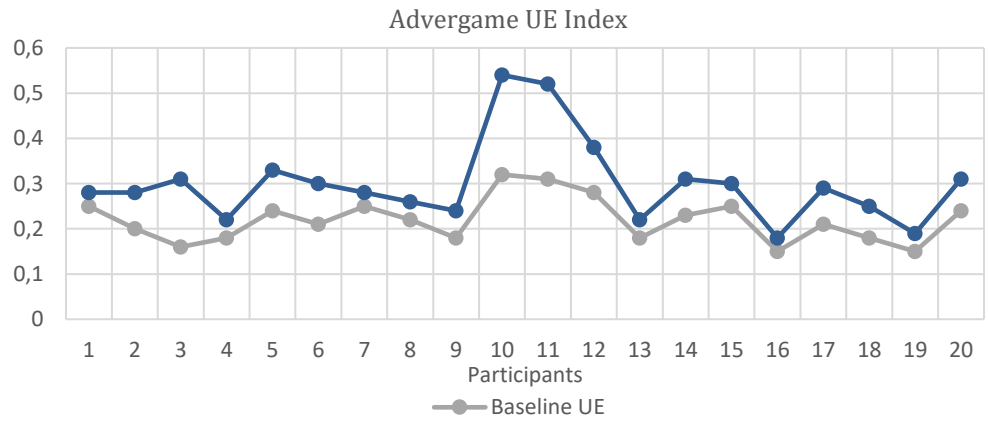


Figure 31: UE index during the Advergame interaction

Regarding the TV commercial, the results in Figure 32 show that in some cases, the EEG engagement index is lower than the baseline period, thus showing a decrease in attention and vigilance, in other words, a lower UE.

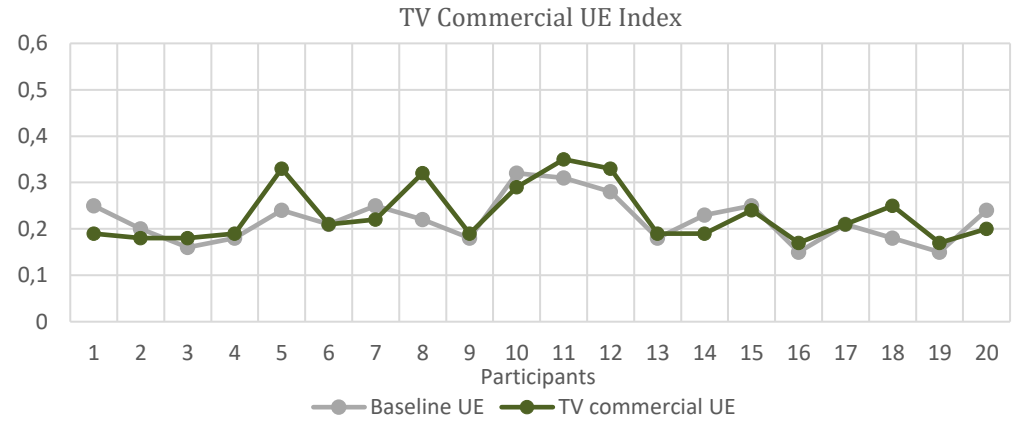


Figure 32: UE index during the TV commercial

The average purchase intention for each advertisement and participant is shown in Figure 33. In the case of the TV commercial, the UPI was higher for only 30% of the participants compared to the original UPI reported at the beginning of the experiment. For the Advergame, the results show that the UPI was usually higher (70% of the cases) than the original UPI before the advertising interactions; this indicates that the Advergames generates a post-game response that tends to influence the purchase intention/reaction of the participants positively, encouraging them to consume the product.

In some cases, however (participants 7, 14, 18, and 20), the purchase intention was higher after seeing the commercial in contrast to the original UPI and Advergame, indicating that for a minority of participants, the traditional advertising has a higher incidence on the UPI. Additionally, it is interesting to notice that for three participants (9, 12, 19), the original UPI was higher than the UPI reported after the Advergame and TV commercial activity, representing a negative influence of both the advertising on them. Thus, considering the total contribution of both advertising, 25% of the participants reported a positive UPI response for both types (Advergame and TV commercial), while 15% reported a negative response. Advergames overall generated the most significant positive responses from the stimulus.

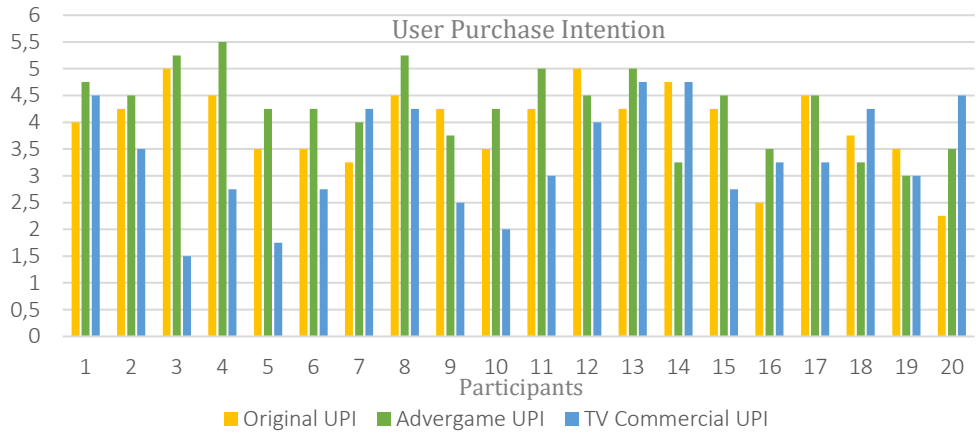


Figure 33: User Purchase Intention UPI before and after the advertising interactions

4.5 Discussion

The results support the initial hypothesis: "*A more interactive type of advertising impacts the user perception and Engagement, positively influencing the purchase intention*". The outcomes show that a more engaging type of advertising significantly influences the UE; in this case, an Advergame has a more significant influence on the UE than a traditional TV commercial. An analysis of the variance (ANOVA) on the EEG engagement index was done in order to verify the statistical difference between the EEG engagement index while playing an Advergame vs. seeing the TV commercial, obtaining: ($F(1,38)= 7,40$, $p < 0.01$). This result indicates that the EEG engagement index was statistically significantly higher when the participants interacted with the Advergames than when they watched the TV commercial.

Still, the fact that a stimulus produces a more engaging behavior would not necessarily imply that the UE will reflect similarly on the UPI. Hence, to analyze if a more interactive type of advertising generates a more significant influence on purchase intention, an ANOVA was also performed for the average purchase intention of the participants for both activities, obtaining: ($F(1,38)=10,75$, $p < 0,01$). The previous result shows that after playing the Advergame, the UPI was statistically significantly higher than the UPI after seeing the TV Commercial.

The interactions between UE and UPI can be distributed in four clusters according to the participants' responses. For the context of this study, we have developed a four-quadrant model (Figure 34) to show the classification

considering the reported Purchase Intention and the EEG Engagement Index Variation.

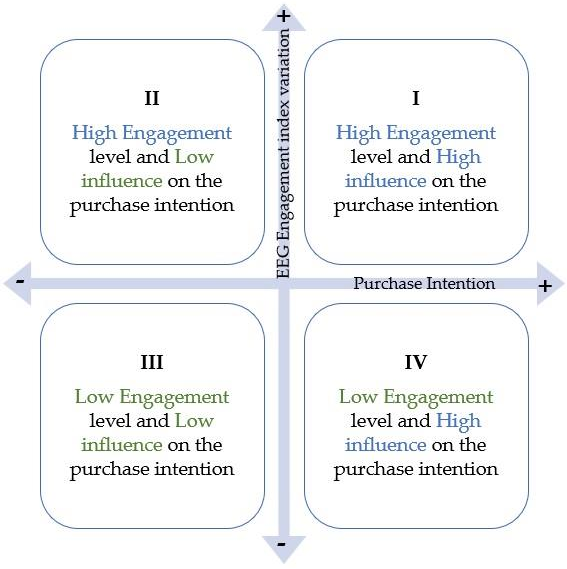


Figure 34: Quadrant model of EEG engagement index variation vs. UPI

The X-axis refers to the UPI; number 4 is located at the center since it indicates the neutral response of the participants in the questionnaire. The Y-axis shows the difference between the EEG engagement index during the stimuli and the baseline. By comparing the difference between the resting period (baseline) and the advertising interaction during the experiment, it is possible to identify the variation of the index; in other words, if the variation is positive, the stimuli produced an increase in the Engagement and vice versa.

For the Advergame (Figure 35), all the participants presented a positive variation in the EEG engagement index, indicating an increase in the UE when interacting with it. In the first quadrant, there are thirteen participants (65%); in the second quadrant, there are seven participants (35%); and in the third and fourth quadrants, there are no participants.

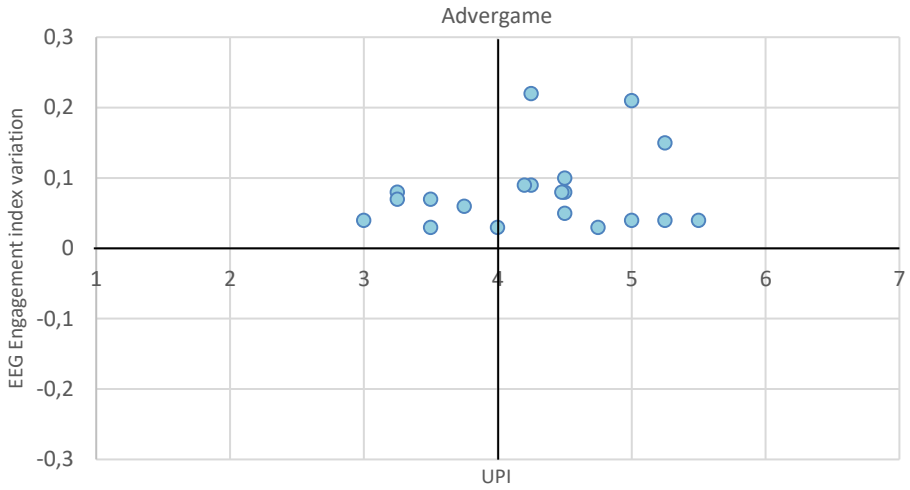


Figure 35: Advergame - Quadrant model of EEG engagement index variation vs. UPI

For the TV Commercial (Figure 36), positive and negative changes in the index were identified, which means that in some cases, there was a negative variation of the EEG engagement index, and in other cases, there was a positive variation. In the first quadrant, there are three participants (15%); in the second quadrant, there are ten participants (50%); in the third quadrant, there are five participants (25%), and in the fourth quadrant, there are four participants (20%).

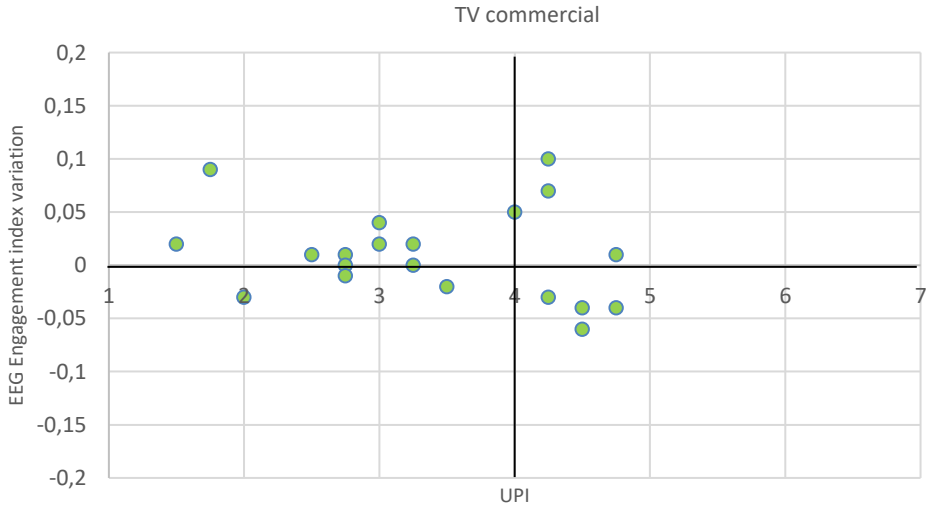


Figure 36: TV Commercial - Quadrant model of EEG engagement index variation vs. UPI

The results in Figure 36 confirm a decrease in the number of participants located in the first quadrant for the TV commercial compared to the results obtained in the Advergame, indicating that a lower number of participants presented a high level of Engagement and a high UPI while watching the traditional ad. In the second quadrant, there is a similarity in the number of participants between the TV Commercial and the Advergame, indicating a high level of Engagement and a low purchase intention; this result suggests that even if the participant was engaged, the advertising did not affect the UPI of these participants. Only the TV Commercial had participants in the third quadrant, showing that traditional advertising is sometimes not attractive. Finally, in the fourth quadrant, the TV Commercial involved four participants who experienced a decrease in the EEG engagement index but still reported a positive purchase intention. These persons located in the fourth quadrant reported a positive attitude toward the brand at the start of the test, confirming the study done by Nelson et al. [300], who indicated that users that have a positive attitude toward the brand or product advertised in games have a more significant influence on purchase intention.

4.6 Conclusions

This study aimed to explore the Engagement and its influence on the purchase intention using a physiological tool, specifically EEG. According to the literature, most studies implemented self-report methods to identify the relationship between video games and UE. Also, no previous studies have analyzed the UE during an Advergame and its implications on the UPI compared to traditional advertising using EEG.

The study's objective was to verify if a more interactive and engaging type of advertising affects the participants, influencing their purchase intention positively. In general, by the results obtained through EEG and the EEG engagement index, it is possible to define that a more interactive and engaging type of advertising creates a higher UE in the participants. Therefore, it is verified that the Advergame always increases the level of concentration, surveillance, attention, and Engagement of the participants while playing. The graphic correlation between the EEG engagement index variation and the UPI presented in the four-quadrant model shows that most of the time, a more interactive and engaging type of advertising influence positively the UPI. In the case of the Advergame, the average purchase intention was higher than the obtained in the TV Commercial (AVG UPI: 4.275 > 3,36), indicating a

more substantial influence of the Advergame in the post-advertising purchase intention.

The proposed four-quadrant model is a valid aid for understanding better the relation between the UE and the UPI, allowing to allocate the users in four states: I) high level of Engagement and high UPI, II) high level of Engagement and low UPI, III) low level of Engagement and low UPI, and IV) low level of Engagement and high UPI.

Additionally, the results confirm some of the Advergame advantages identified by Mendiz [259]; Advergames offer high exposure to a brand or product because the participants are in constant contact with them compared to traditional advertising; hence the participants' levels of Engagement are higher when interacting with Advergames, maximizing user attention. Similarly, we validated the statement by Goh and Ping [264], proving that users' previous attitudes toward the brand positively influenced the UPI.

We can conclude that it is essential to consider the Users' Engagement as a parameter to improve advertising campaigns and significantly influence the users, attracting them to a product or brand. Equally important is the right choice of the methods (self-report and physiological) implemented to perform this kind of analysis.

Advergames can have both benefits and drawbacks when it comes to user experience and enjoyment. On the positive side, advergames can provide an interactive way for users to engage with a product and enhance their experience. However, the inclusion of ads could also impact the user experience and enjoyment level if the ads are intrusive or irrelevant. For example, if ads are placed in a way that disrupts the gameplay or if they are not pertinent to the user, it can lead to frustration and a negative perception of the overall advergame experience. Thus, the benefits and drawbacks of advergames largely depend on how well the ads are designed and integrated and how they are perceived by the users. In this regard, the analysis of users' perceptions through physiological methods, such as EEG, can offer further considerations to improve the ads' design.

This chapter presents a use case and validation of EEG-based quantitative indicators in advergames, which can be used alongside self-report methods to minimize biased responses. In this research, the experimental setup included a specific Advergame and TV commercial; consequently, the results might differ

depending on the advertising to which participants are exposed and the degree of affinity with the product or brand. Yet, the methodological analysis and the results obtained can be equally considered for similar products; in this sense, there is a research opportunity to explore additional contexts and experimental scenarios in order to increase the validation value. One potential future research topic could be the EEG analysis of the different design features within the advertising development; characteristics such as colors, sounds, motion, and forms, could be investigated independently to study to which extent these stimuli could influence the users' perceptions. By measuring brain activity, researchers can gain a better understanding of how these factors influence engagement with advertisements. For example, how different colors and musical styles in ads affect attention and memory, or how the use of motion in ads affects the ability to retain information. Likewise, a further research goal is the ecological validity analysis in the real world to understand how well the results of the experiments reflect real-world conditions. In this way, we may be able to develop more effective strategies that better engage audiences and improve the effectiveness of advertisements.

The methodology presented in this research can be replicated in similar studies interested in deepening the UE analysis. This study is expected to provide practical evidence and theoretical foundations for new approaches to user perception analysis. The results of this investigation have been published and can be consulted at https://doi.org/10.3390/electronics12010122 [301].

Chapter 5

Interpreting Emotions with EEG: a study of emotional responses to Chromatic and Form Variations in VR

As explored in the previous chapters, practitioners and researchers are still in pursuit of creating products that are both functionally satisfying and emotionally enticing. In this sense, users' engagement monitoring during the human-product interaction provides significant information to enhance the design process. While still, traditional self-assessments are the most common method to assess users' perceptions, technological advances are making other methods able to measure respondents' behavior. This study aims to continue exploring EEG as a method to assess and interpret emotions. To do this, we created seven different virtual environments (VEs) as a stimulus presented in virtual reality (VR); three characterized by different design spaces with seven chromatic variations, and four VEs defined by their boundary form protrusion and curvilinearity. This research aims to analyze how scenarios' changes in color and form influence participants' emotional responses, specifically on Valence, Arousal, and Engagement dimensions. The findings suggest that color and form variation influences users' emotions and that EEG outcomes could support emotion interpretation. This study provides useful information regarding the potential of EEG to explore users' emotions during product design and development.

5.1 Introduction

During human-product interaction, Hekkert [302] defined three types of Product Experience: aesthetic pleasure, attribution of meaning, and emotional response. The emotional experience relates specifically to the feelings and emotions elicit-ed during the interaction with a product. Norman [303] proposed that the emotional response toward a product can be split into three components: reflective, involving high-level cognitive processes, behavioral, related to the execution of routine tasks and skills, and visceral, an automatic and elementary response of human beings. All these dimensions shape the perception of the user toward a product and the product design itself. This way, emotions model the user's acceptance of a new product; therefore, to build successful products, the product design and development process should consider not only the users' requirements and wish-es but also their perceptions and emotions during and after an interaction with a product, system, or service. In this regard, Pallasmaa et al. [304] note that built environments carry emotional qualities, as these emotional descriptors are well documented in the architectural discourse and should be further examined with specific tools developed in cognitive sciences.

Emotions are often described as feelings concerning a specific phenomenon, such as a mood or a sentiment. Many studies have used almost exclusively self-report measures to study the users' emotions; however, technological advances can make other kinds of measurement more plausible. For example, self-reported measures can be contrasted to other experimental methods that do not rely only on respondents' reports, for example, physiological approaches that can measure respondents' behaviors in a constrained or controlled environment. The inclusion of physiological parameters provides information that allows researchers and product designers to determine whether self-reports' findings are trustworthy and representative to find the "ground truth" of the emotion [305]. In this order, the product design will benefit from meaningful data to enhance its development process.

EEG is a promising tool to measure user emotions. By analyzing EEG data during users' exposition to a stimulus, studies have shown that EEG can provide metrics for determining different emotional traits and indicators [12], [306]. Concerning emotions, empirical studies have confirmed that colors and geometric form variations in built environments might evoke positive or negative feelings and influence users' moods and emotions [306]–[308].

This study explores the EEG as a method for emotion interpretation using chromatic and geometric form scenario changes as the stimulus. To do this, we have created seven different Virtual built Environments (VEs), of which three are developed to investigate chromatic variations and the remaining four the form variations. Subsequently, all VEs are presented as virtual reality (VR) scenarios, where participants are welcome to navigate every VE, while recording their reactions with an EEG headset.

The color VR scenarios are characterized as three different VEs: an open plan apartment, an industrial loft, and an outdoor space, where their chromatic lighting changes, passing through white, yellow, orange, red, violet, blue and green. The form VR scenarios are characterized as four VEs, according to their geometric boundary form manipulation dictated by the parameters of protrusion and curvilinearity, named: rectilinear, angular, blobby, and curved.

This study aims to explore whether the stimulus variation in terms of chromatic and geometric form scenario changes can evoke an emotional response affecting the users' perceptions. In this research, VR is intended to be an interactive and enabling instrument to support EEG analysis for emotion interpretation.

5.1.1 The Representation of Emotions

Emotions allow us to relate to other people and express our behavior towards others and our environment. The emotional response can be caused by several factors that stimulate us, such as a behavioral factor or an automatic response. To explain these concepts, Russell [309] developed the circumplex model of affect (Figure 37), a 2D emotion space structured to express emotions through two dimensions: Valence and Arousal.

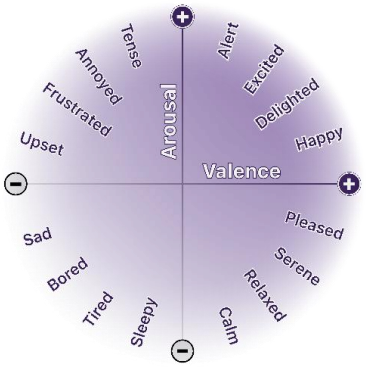


Figure 37: Circumplex model of affect

Arousal expresses the activation level of the emotion (ex. more or less calm or agitated), and Valence is the level of pleasantness or unpleasantness concerning a perceived stimulus. Furthermore, UE, a typical emotion in the context of human-computer interaction, has been a matter of interest for enabling interfaces to adapt to users [310]. It can be interpreted as the level of involvement and absorption into an activity, and it can give us further information for analyzing the users' perspective during the product interaction. In particular, for this study, we focus our attention on the definition of cognitive Engagement, as it reflects the idea of mental workload and willingness to execute a task [262].

5.1.2 Overview of Color and Boundary Form Influence and EEG Emotions Interpretation

The literature shows that the chromatic influence of the colors is still a matter of research; authors have explored how colors stimulate capacities of excitement for warmer shades or calming ones for colder ones [311]. In a recent study [312], the authors proposed a methodology for creating VR scenarios, oriented to elicit emotions and stated that bright saturated colors are usually related to high Valence and Arousal, less saturated colors to calm, and red color can be associated with anger. Likewise, similar studies have concluded a significant variation while changing scenarios typology [308], a greater level of emotional pleasure in the more colorful work built environments [311], and different emotional relationships according to the color analyzed. Disgust prevailed in the color red; happiness was the most widely expressed in the green, while, in the blue, the reactions remained neutral [307].

Similarly, research on the affective qualities of geometric forms in built environments is an ongoing investigation; the studies demonstrated that variables of boundary form curvilinearity, protrusion, and ceiling height influence emotions [313], [314]. Elements in form curvilinearity in objects are of particular interest as they have been associated with positive emotions in contrast to angularity [315], and users evidenced to have an unconscious perceptual preference towards curvilinear spaces [316], independent of an individual's culture, educational level, or design expertise [317]. Research into the emotional affect of form features such as the number of protruding edge points, protruding form surface, curvilinear smoothness, and symmetry of objects have demonstrated to yield positive and negative Valence, low and high Arousal, and calm and chaotic emotional responses [318]. Additionally, a study on ceiling height variations in enclosed spaces suggests that high ceiling height scenarios consistently score higher pleasantness scores

when compared to their lower ceiling height counterparts [319]. Likewise, Coburn et al. [320] suggested examining design variables in architectural scenes such as enclosure, ceiling height, and curvature to evoke a distinct neural response related to psychological dimensions of coherence, fascination, and hominess.

Regarding the use of EEG for emotion interpretation, studies have shown that EEG can provide metrics for determining Engagement, Valence, Arousal, and other indices helpful in understanding human behavior. McMahan et al. [12] compared three Engagement indices during videogames play using an EEG system. They concluded that EEG could measure the users' level of Engagement while playing and suggested it as the most suitable index for future studies according to their findings. In addition, the authors identified the need for further validation by exploring and analyzing this methodological approach in other research fields. Suhaimi et al. [321] performed an EEG study to measure the participant's reactions to visual stimuli intended to provoke different emotions. After each stimulus, they asked the participants to complete a self-assessment questionnaire and collected EEG data for posterior correlation and classification. Similarly, Hu et al. [322] aimed to correlate ten emotions using a self-report questionnaire and EEG; the authors, however, recognized the subjectivity of the participant self-assessment, concluding that this is still an open scenario for research. Moreover, Ramirez et al. [286] have conducted studies to analyze the effects of music during health treatments; in these studies, the authors have computed and validated the Valence and Arousal indices for obtaining information about the patient's emotional state. Finally, the systematic review by Ismail and Karwowski [323] can be considered a valid synthesis of the EEG indices and trends used for measuring human cognitive performance.

Although there have been advances in research in this field, many of these studies have been conducted using self-assessment reports as a means to evaluate the users' responses, which, despite being an agile and supportive tool, rely solely on the answers consciously indicated by the evaluated subject, tending to subjectivity and a lack of validation of the user's primary emotional response [308], [321], [322]. In this sense, there is an opportunity to investigate EEG to attain quantitative results in design-related fields.

This study investigates the usage of EEG for emotion assessment with the goal of contributing to bridge a gap derived from the literature, in which self-reports appear to be the mostly adopted emotion evaluation system so far. In particular, it

fosters emotional design research by analyzing the users' responses to colors and forms using a physiological method, rather than questionnaires, with the ultimate aim of exploring the EEG analysis's pertinence for product design and development, and complementing the findings obtained from previous studies.

5.2 Methods

This study aims to explore EEG as a tool to support emotion interpretation through the analysis of Valence, Arousal, and Engagement indicators, during the exploration of three VR scenarios characterized by color changes (white, yellow, orange, red, violet, blue and green) in combination with different design styles (open plan, industrial loft, and outdoor space) and four VR scenarios characterized by form changes (rectilinear, angular, blobby and curved) in combination with ceiling height variations (high and low).

5.2.1 EEG as a Physiological Tool for Understanding Users' Emotions

EEG detects and records the brain's electrical activity. According to the user's situation, the brain's nerve cells generate electrical impulses that fluctuate rhythmically in different patterns. This study was conducted using the Emotiv EPOC+, a mobile EEG Instrument composed of 14 saline-based electrodes located according to the international 10-20 sensor placement system [298].

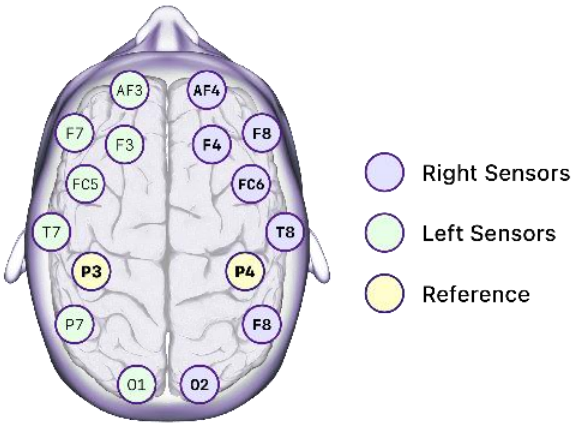


Figure 38: Sensor locations

The sensors are at positions AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2, and two additional CMS/DRL reference channels (Figure 38) at P3 and P4. The sampling rate is 128Hz, and the bandwidth is 0.2 - 45Hz.

The electrical EEG signal is composed of different frequencies produced by neuronal electrical activity; these frequencies, known as bands, are classified as Theta (θ) (4–8 Hz), Alfa (α) (8-12 Hz), Beta (β) (12-25 Hz), and Gamma (γ) (25-45 Hz). Each type of band reflects specific and different cognitive processing skills in specific brain areas [98]. The theta (θ) waves are associated with lower mental activity or meditative states; the alpha (α) waves are related to relaxation and usually appear in a sleep-wake cycle. In contrast, the Beta (β) waves describe a system activation and alertness, and Gamma (γ) waves learning and information processing.

Alpha (α) waves are associated with calmness and relaxing states, and in addition, they have been related to brain inactivation. Beta (β) waves are dominant when attention is directed towards a task or when a person is alert and engaged in mental activity. Hence, the beta/alpha power ratio (Equation 6) is considered an appropriate indicator of the Arousal state [287], [288]:

$$Arousal = \frac{\beta F3 + \beta F4}{\alpha F3 + \alpha F4} \tag{6}$$

Moreover, EEG studies have shown that the right brain hemisphere is dominant for negative or unpleasant emotions and that the left hemisphere is dominant for positive or pleasant emotions [286]. It has been suggested that it is an indication of motivational direction. Thus, for analyzing Valence, this study used the frontal alpha (α) asymmetry index to evaluate the hemispherical activation in the frontal lobe related to emotion regulation (sensors F4 and F3) [324] by subtracting the natural log of the left hemisphere alpha power (αF3) from the natural log of right hemisphere alpha power (αF4) and comparing their difference:

$$Valence = \alpha F4 - \alpha F3 \tag{7}$$

Since alpha (α) power is inversely related to regional brain activity, decreased power values of the alpha (α) band indicate an increase in cortical activation, so higher scores in Equation 7 indicate relatively greater left frontal activity (increased Valence) and lower scores relatively greater right frontal activity (decreased

Valence) [325]. Similarly, higher scores in Equation 6 indicate an increase in Arousal states.

Considering that Beta (β) power is related to an increase in brain activity during mental tasks, and alpha (α) and theta (θ) activity are related to lower mental vigilance (theta (θ) brainwaves occur most often in sleep), as previously stated, in the study carried out by Freeman et al. [99] the authors validated the EEG Engagement index (Equation 2). In this way, by comparing the initial state with a post-stimulus-response, it is possible to identify the Engagement variation; if it increases, a higher Engagement and sustained attention is expected.

$$Engagement = \frac{\beta}{\alpha + \theta} \tag{2}$$

In this study, each participant's Engagement index was calculated using the averaged measurement from all sensors.

5.2.2 Data Analysis and Feature Extraction

For data analysis, a bandpass filter and Fast Fourier Transformation were performed; the band power (μV^2) calculation was done at 0.125-second intervals (8Hz). A Hanning window was applied to reduce noise artifacts from the FFT procedure. And the squared magnitude of the complex FFT value was averaged across the frequency bins in each band. Equations 2, 6, and 7 were employed for emotional metrics assessment. For Valence and Arousal, EEG data was analyzed in 4 locations on the prefrontal cortex: AF3, AF4, F3, and F4.

It is important to highlight that there are no absolute maximum or minimum levels for Arousal, Valence, and Engagement since these values vary from person to person. For this reason, this study used a "within-subject design" experiment commonly employed in the EEG research field [326], [327]. As well as in other physiological methods (ex. GSD and heart rate), the EEG measurement is divided into two phases; the first one consists of baseline data to control the initial subject response, and the second contains the electrical brain activity measurement while carrying out a task (stimulus). By comparing the difference between the baseline and the stimulus during the experiment, it is possible to identify the activation response and, therefore, the increase/decrease of the emotional metrics [324].

5.2.3 Experiment Setup

Recent studies have established the potential of VR to elicit emotions by creating multisensorial and interactive environments [312]; however, despite the exponential increase in the implementation of VR in different fields, studies relating to EEG-based emotional classification are not commonly researched using VR as the stimulus [321]. Therefore, considering the possibilities that VR applications can give to the emotional analysis and that EEG used simultaneously in VR experiments is still an open research opportunity, we wanted to create an immersive experience for the participants and explore the EEG for emotion monitoring. Specifically, this research used VEs presented in VR as a stimulus to analyze with EEG if color and form variations in the VR scenarios might or might not elicit emotional responses, as previously claimed by studies that used only self-reports. In this sense, the study's objective is to explore the EEG as a method for detecting and monitoring the visceral emotional responses elicited by color and form variation through the analysis of Valence, Arousal, and Engagement quantitative indicators.

The study conducted by Dozio et al. [312] provides a framework for the creation of affective VR scenarios. According to these guidelines, our compositions included natural and concrete elements like mountains, forests, and furniture and abstract elements, including chromatic variation, which is of interest to this study. To elicit emotions in VR with the broadest possible spectrum, we have created three VR scenarios characterized by different built environments (an open plan apartment, an industrial loft, and an outdoor space) and added visual elements that include the use of colors, lighting, and furniture. Additionally, openings were used to express the time of the day (dark or bright) and the weather conditions. The design approach and element arrangement of each color scenario was based on recommendations [312] suggested to elicit neutral emotional responses in VR. Within each scenario (Figure 39), six primary colors (Yellow, orange, red, violet, blue and green) with the addition of white were selected for this work, varying according to the environment's chromatic lightning, that change every 30 seconds. The final color scenarios were designed and created using Blender 2.92 and later exported to Unity.

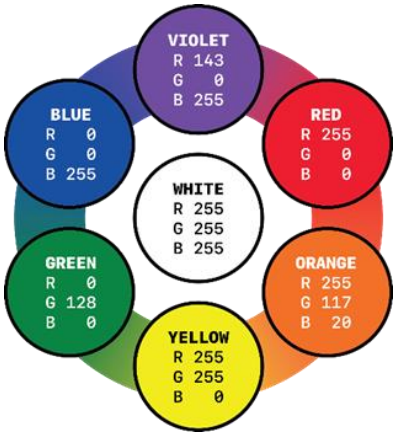


Figure 39: Color Selection

Jointly, experiments done by Shemesh et al. [313] and Franz et al. [314] were used as guidelines to compose VEs with boundary form variations. For this study, the form scenarios were not conceived with a static observation but rather in motion, where the composition of the VEs was placed in straightforward linear space syntax. A scripted movement following the space syntax allowed us to consistently examine the perceptual contribution of individual form variations between scenarios. Each form scenario was paired together with its high ceiling height (6 meters) and low ceiling height (2.1 meters) counterpart. Each scripted movement of each scenario's ceiling height variation lasted 30 seconds and was separated with a controlled environment lasting 3,5 seconds. Geometries were generated using grasshopper (plug-in for Rhino 7.0) to ensure that each form scenario followed identical parameters of form manipulation and that geometries generated were never identical yet followed a consistent program. The final combination of all scenario pairs was later randomized for each participant following a Latin square sequence and later exported in Twinmotion 2022.2.

The three color scenarios were created as described here below.

Open Plan. (Figure 40a) For the first VR scenario (VR1) its VE was designed to be brightly lit and planned after a typical open-plan apartment living room. The posterior-facing wall consisted of a floor-to-ceiling window, where the view simulated a partially sunny day with blue skies.

Industrial Loft. (Figure 40b) For the second VR scenario (VR2) its VE was created in a moderately lit environment, where the floor-to-ceiling windows were over-looked by adjacent urban buildings. The climatic conditions were defined as a rainy cloudy day with poor external visibility.

Outdoor Space. (Figure 40c) For the third VR scenario (VR3) its VE was conceived at nighttime as a shelter in the middle of a desert, with furniture design and arrangement following minimalistic design language, with no discernable walls that delimit movement.

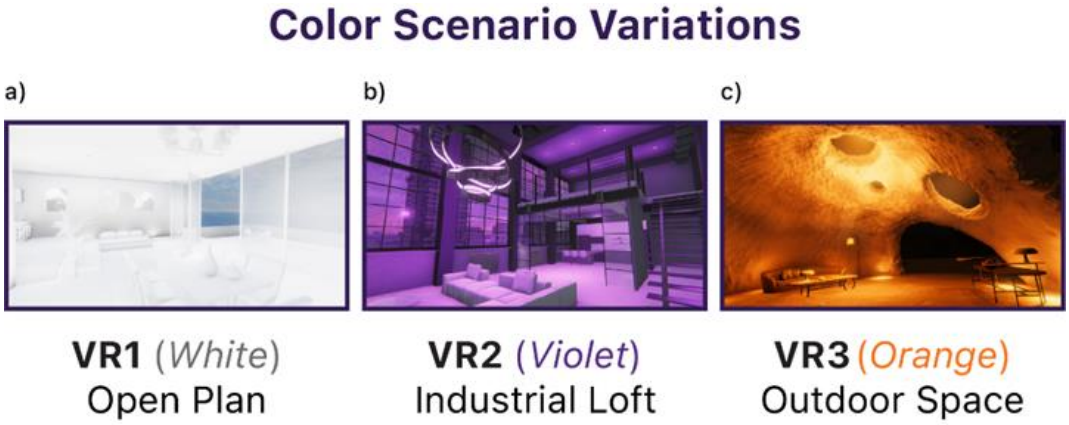


Figure 40: Color Scenario Variations. (a) VR1 Open Plan in the white variation. (b) VR2 Industrial Loft in the violet variation. (c) VR3 Outdoor Space in the orange variation.

To test the emotional response derived from form variations, a space syntax of VEs was required to test how elements of boundary and edge curvilinearity and protrusion elicit an emotional response. This means that the four form VR scenarios followed the same space syntax named Dynamic clusters (Figure 41), where the scripted movement transported the participants forward; passing them through an empty enclosed built environment, following with a transition to an outdoor environment where it was populated with a grid of geometries (16x4) of various sizes, leading into an unobstructed clear and open space. Continuing, the participants were moved through the open space, where it was later followed by a secondary outdoor population of geometries that concluded into a secondary empty enclosed environment. Each scenario composed their dynamic cluster in pairs determined by their ceiling height, starting with the first cluster having a ceiling height of 6 meters and a secondary low ceiling version of 2.1 meters. Each dynamic cluster started and ended with a portal separating them with a control room of 20 meters in width and length and a ceiling height of 6 meters in rectilinear form.

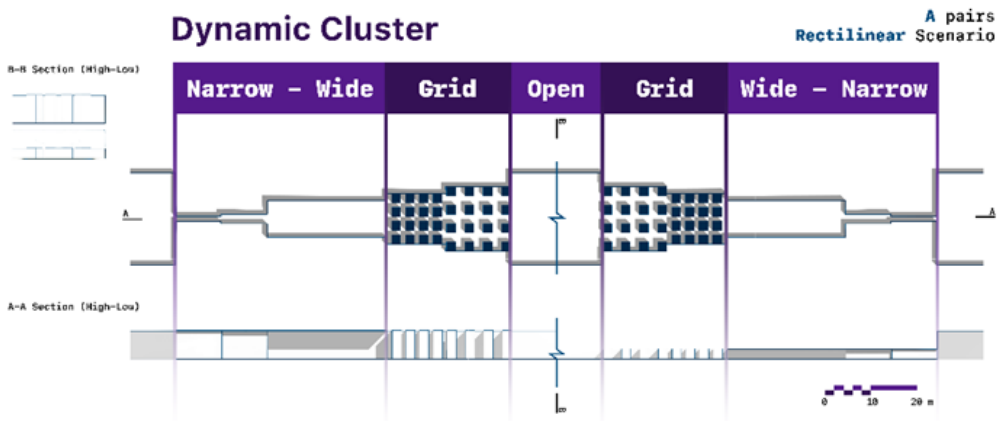


Figure 41: Plan and section of the of the A pairs Dynamic Cluster

Rectilinear. (Figure 42a) For the first VR scenario (A pairs) the VE followed the dynamic clusters' space syntax and generated forms with no edge protrusion or boundary curvilinearity.

Angular. (Figure 42b) For the second VR scenario (B pairs) the VE similarly generated forms with no boundary curvilinearity but rather with edge protrusion.

Blobby. (Figure 42c) For the third VR scenario (C pairs) the VE was created where the generated forms had both edge protrusion and boundary curvilinearity.

Curved. (Figure 42d) For the fourth VR scenario (D pairs) the VE was conceived with forms that had boundary curvilinearity and no edge protrusion.

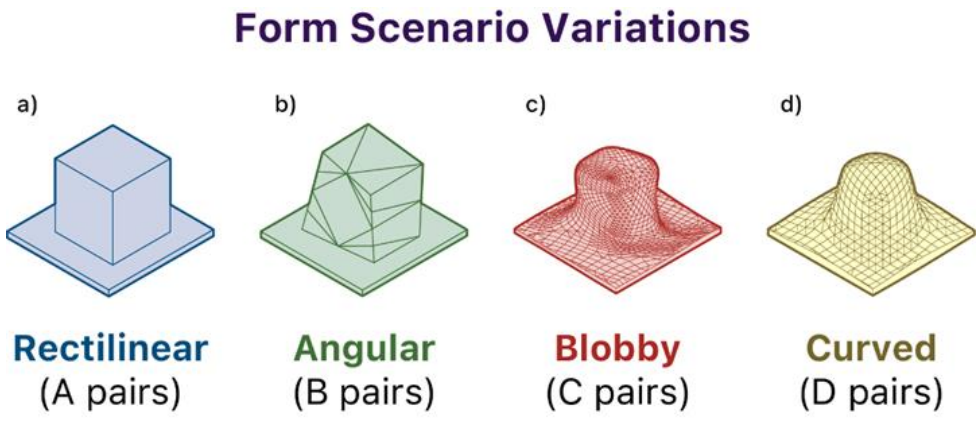


Figure 42: Form Scenario Variations. (a) Rectilinear: No edge protrusion, No boundary curvature. (b) Angular: Yes edge protrusion, No boundary curvature. (c) Blobby: Yes edge protrusion, Yes boundary curvature. (d) Rectilinear: No edge protrusion, Yes boundary curvature

All form VR scenarios were created as soundless with monochromatic untextured surfaces, with climatic conditions simulating a sunny midday blue clear sky.

Our study consisted of a controlled experiment carried out in a laboratory setting (Figure 43), ensuring identical lab conditions. For the color scenarios, we recruited 34 healthy participants, 14 identified as female (41%) and 20 identified as male (59%), aged between 20 to 30. For the form scenarios, we recruited a total of 39 participants, 17 identified as female (44%) and 18 as male (56%), between the ages of 20 and 48. All participants were informed about the experiment, the protection and use of their data, and were given an informed consent to sign. Then, each participant was invited to a closed room equipped with an adjustable comfortable chair, a large screen, and a gamepad used to navigate across scenarios. Following up with a demographic questionnaire and headset setup, proceeding with recording the participant's initial baseline, during eyes-closed condition, and subsequently left alone in the room. All the participants (one at a time) executed the test in the same room where all light sources besides the screen were turned off or masked to facilitate maximum immersion and adequately run the experiment.

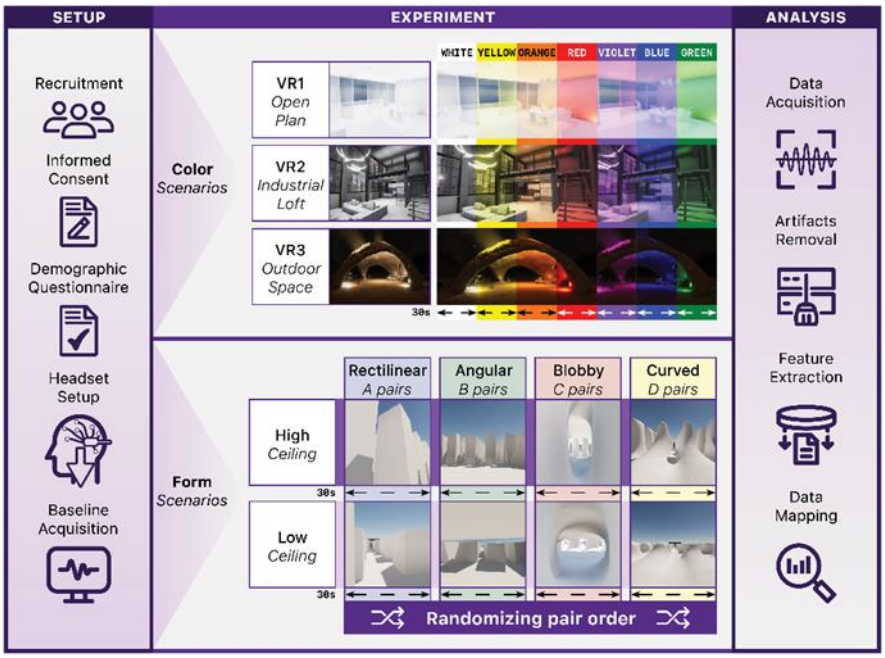


Figure 43: Experiment procedure. Starting with an initial setup followed by the two experiments where the color scenarios were separated based on their built environment location and the form scenarios were dependent on the pair order, and final data analysis.

For the color VR scenarios, each participant was encouraged to explore the three scenarios freely while measuring their brain activity with the EEG headset. In each scenario, there was a color change every 30 seconds. The test was carried out without interruptions between changes in scenarios and colors. At the end of every stage, an automatic marker was placed. The total duration of the experiment is about 12 minutes plus the headset setting time.

Similarly, in the form VR scenarios, each participant was given a randomized pair order distributed equally with the demographic factors. Each participant was given a gamepad where they were allowed to look around the scenario during the experiment and reassured that if they released the controls their viewpoint will reset into the original forward direction of movement. Each Dynamic cluster lasted 30 seconds, where an automatic marker was placed. The total duration of the form scenario experiment lasted around 5 minutes and a total of 15 minutes including the initial setup.

5.3 Results

The data was analyzed and processed, major artifacts such as ocular (EOG) and muscular (EMG) were removed. Considering the dataset signal quality, and only healthy participants that finished completely the test with no interruptions, from the sample of 34 participants for the color VR scenarios and 39 of the form VR scenarios, 30 and 31 results respectively were considered valid for this study. The EEG data was segmented into 30s epochs according to the color and form stimulus interval and scenario. Then, for each participant, the emotional indicators (Arousal, Valence, and Engagement) for each scenario and color/form variation were extrapolated from the EEG data. The baseline data was extracted and then subtracted from the post-stimulus response; this way, it was possible to analyze the contribution of the individual stimulus to the emotional response. To avoid skewness [328], the median was analyzed to measure the central tendency of our data set.

Considering the entire color contributions as a whole and comparing only the variation of scenarios (Figure 44a), from the examination of global values, it emerged that the Engagement was higher in the VR3, an outdoor space where a shelter within an area with no boundaries, and lower in the VR2, an industrial loft situated as an urban building in a raining day, while in the VR1, an open plan apartment, the Engagement barely increased. The Arousal was equivalent in VR1 and VR3 but decreased in VR2, while the Valence gradually decreased as long the

test was carried out. Considering the color changes (Figure 44b), the findings show that the more engaging colors are white and red, followed by yellow, violet, and blue. At the same time (computing the responses from all scenarios), orange and green contributed to an Engagement decrease.

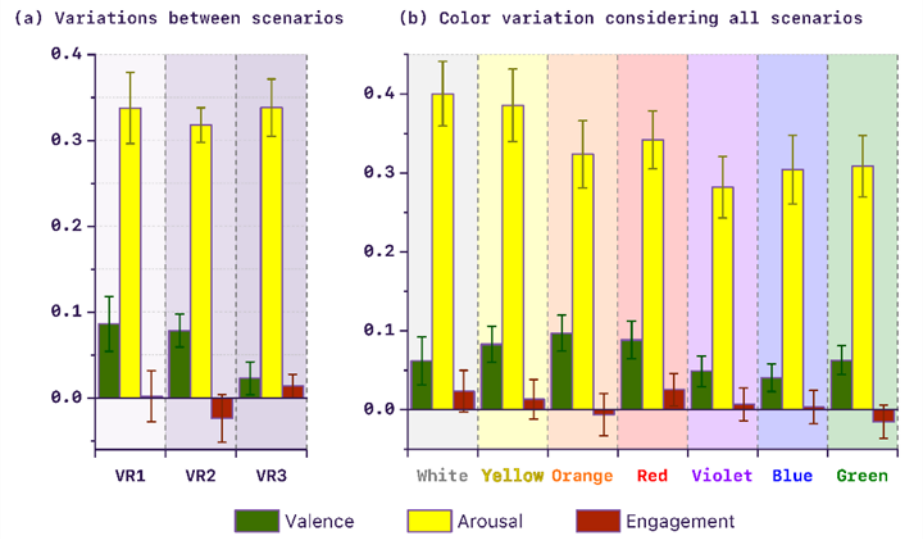


Figure 44: (a) Variations between scenarios (b) Variations between colors. SD is shown for each condition. Highest SD=0,046 for Arousal in Yellow, and the lowest SD=0,017 for Valence in Blue.

As for the form scenarios, we divided the form pairs according to their ceiling height version and designated them a letter accordingly; H for the high ceiling and L for the lower ceiling Dynamic cluster. Thus, the data (Figure 45) is coded based on their form variation, AH and AL for Rectilinear forms, BH and BL for Angular forms, CH and CL for Blobby forms, and DH and DL for Curved forms. Initial observations suggest that overall, Arousal levels were consistently higher when the ceiling height was High and dropped after the transition into the Low ceiling height version of those form pairs. Additionally, overall Engagement levels between the ceiling height counterparts in each form scenario increase when the ceiling height gets Lower, apart from the B pairs. Considering the global form variation of each scenario pair, the A pairs (Rectilinear forms) had barely any positive Valence levels, whereas it scored the highest Arousal level in its high ceiling version (AH) in contrast to all other high ceiling scenarios.

Additionally, Engagement levels scored the lowest in the high ceiling version (AL) considering all other scenarios and were near zero in the lower ceiling height counterpart. For the B pairs (Angular forms), the median Valence and Engagement

levels were consistently rated negative independent of ceiling height, and Valence was the lowest amongst all other scenarios. For the C pairs (Blobby forms), the median valence levels were consistently rated higher in both ceiling heights in contrast to all other scenarios while scoring lowest engagement in both ceiling height versions and lowest in all scenarios except for AH. Additionally, the C pairs scored the lowest arousal scores amongst all form variations, for both their higher and lower ceiling scenario counterparts. Lastly, the D pairs (Curved forms) had overall the highest arousal levels in both ceiling scenarios, except for AH, while having the highest engagement scores amongst all scenario pairs. Notably, while Arousal between the D pairs follows the general trend between their ceiling height variants, the difference between them is insignificant.

Upon further analysis, it reveals how in the cases where only edge protrusion (B pairs) is considered in form variation, they score the lowest in valence levels, whereas a combination with boundary curvature (C pairs) yields the highest valence levels at the cost of decreased engagement and Arousal. Additionally, high ceiling VE where forms lack edge protrusion and curvature (AH), seems to yield the highest scores of Arousal and lowest Engagement, whereas with the introduction of boundary curvature (DH) has a minor reduction in Valence and Arousal and produces not only higher Engagement levels, rather one of the only two positive ones in all form scenarios.

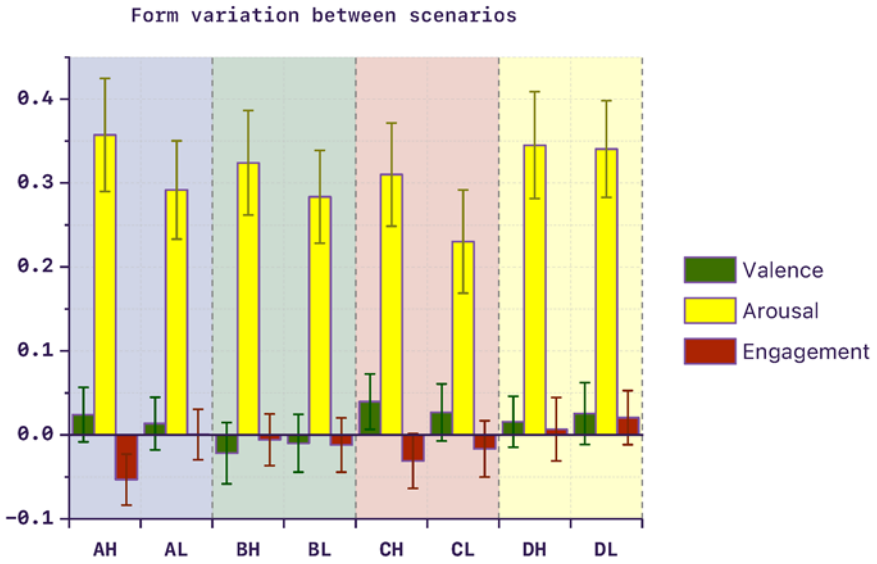


Figure 45: Variations between form and ceiling height. SD is shown for each condition. Highest SD=0,067 for Arousal in Rectilinear forms and the lowest SD=0,030 for Valence in Angular forms.

5.4 Discussion

The results suggest that the weather and lighting conditions affected the participants' Arousal and that the lack of visible spatial limits could increase the task Engagement. Moreover, Valence decrease could be related to boredom or tiredness. Overall, there is a common increase in Valence, Arousal, and Engagement in the center segment of the test (Figure 44b), suggesting that the users feel comfortable with the VR interaction and exploration. The median values of Arousal and Engagement are higher at the beginning of each test, indicating interest and curiosity in interacting with the environment for the first time. Similar to Figure 44a, Valence decreases near the end of the test as people get used to the environment.

By reporting our outcomes of the color scenarios to the circumplex model of affect (Figure 46), it is possible to visualize that white and yellow have the highest Arousal values, and violet and blue have the lowest. Related to Valence, red, yellow, and orange reported the most significant values, while blue was the lowest; these findings are coherent with the warm and cold colors theory described by Küller et al. [311], suggesting that warm colors like red, yellow, and orange are related to stimulating emotions, while cold colors such as blue, violet, and green are considered more relaxing.

Analyzing the specific color contributions inside each VR scenario, the findings show that the Arousal was high for all scenarios at the beginning of the test; this could be explained by the fact that this was the very first contact with the VEs for the participants. On the other hand, the Valence has an increase in the middle section, and then it tends to decrease; the Engagement has a similar tendency, decreasing as the experiment was executed, although this is not explicitly related to the stimuli but to the test length. This result is aligned with the global analysis, suggesting that, even if the Arousal was always positive, the Valence and Engagement are inversely proportional to the test duration. The duration of the test in this type of study can act as a limitation; although an adequate amount of data is necessary for the correct analysis of the information, tests that are too long (according to the objective of the experiment) can affect the results, in our case a 12-minute test reported in the last 2 minutes a reduction of concentration and interest.

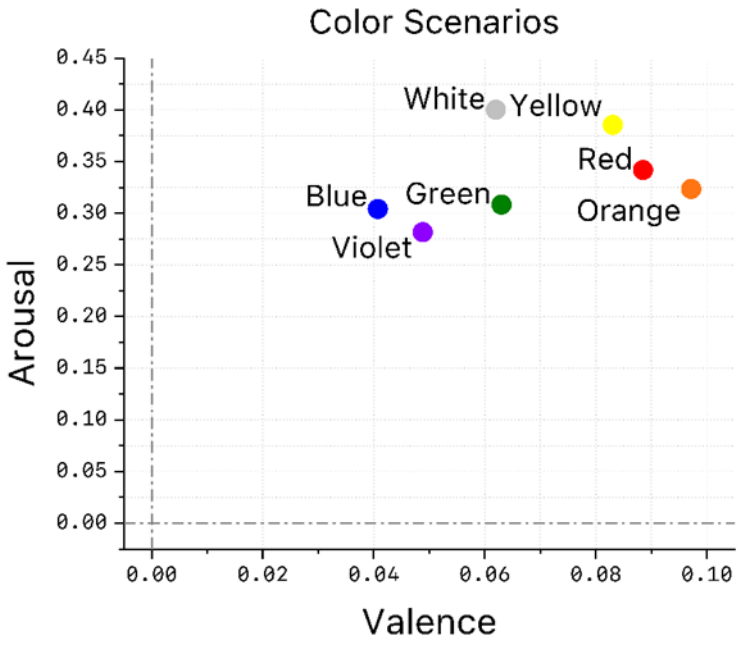


Figure 46: Color stimulus circumplex model of affect

Comparing the results of our experiment with the findings of Stone [308], there are some similarities related to the environmental changes; even if the chromatic variations reported interesting results, the emotional responses were more evident when changing between scenarios. The differences between scenarios' nature, lighting conditions, weather, and spatial limitations prevailed over the chromatic variation exhibited. For instance, the Arousal was higher in the brightest scenarios designed to experience good weather conditions. Regarding the Engagement (an indicator used mainly in the videogames field and less studied in chromatic and form studies), the space design was impactful as well; in the out-door space VR scenario, the Engagement was significantly higher than in the closed spaces. The Valence showed a behavior similar to the Engagement; in general, it was always positive, with an evident growth in the non-extreme stages of each VR scenario interaction.

Similarly, by plotting the outcomes of the form scenarios to the circumplex model of affect (Figure 47), we can visualize the Valence and Arousal levels contribution of all form pairs and plotting a line between each pair's ceiling height variants highlights their relationship. This data demonstrates how elements of curvilinearity, and protrusion influence emotional responses. The initial discovery of higher ceiling height yielding positive levels is consistent with Dai et al. [319]

observations, and the clear negative Valence levels of scenarios where they only manipulate the forms of edge protrusion (B pairs) are reflected in the opposite positive Valence levels when their boundary edge incorporates curvilinearity (D pairs), which is in direct agreement with Silvia and Barona's [315] findings that curvilinearity is always of preference to angularity. While giving definitive answers to any empirical evidence is difficult, possible interpretations can assist in understanding the results. One possible interpretation of those results is considering that repetitive rectilinear forms (A pairs) do not evoke any discernible emotional reactions to observers, but rather decrease when they transition to the low ceiling counterpart, as they do not feel the need to engage with the visual perception of those physical properties. A possible explanation of this is related to the daily interaction of observers with the real world, where urban landscapes are populated with buildings that mimic the forms in the A pairs. This explanation also demonstrates how unusual built environments that utilize forms with edge protrusion (B pairs) in combination with curvature (C pairs) elicit stronger emotional responses and engagement, in contrast to expected predictable forms experienced in everyday life.

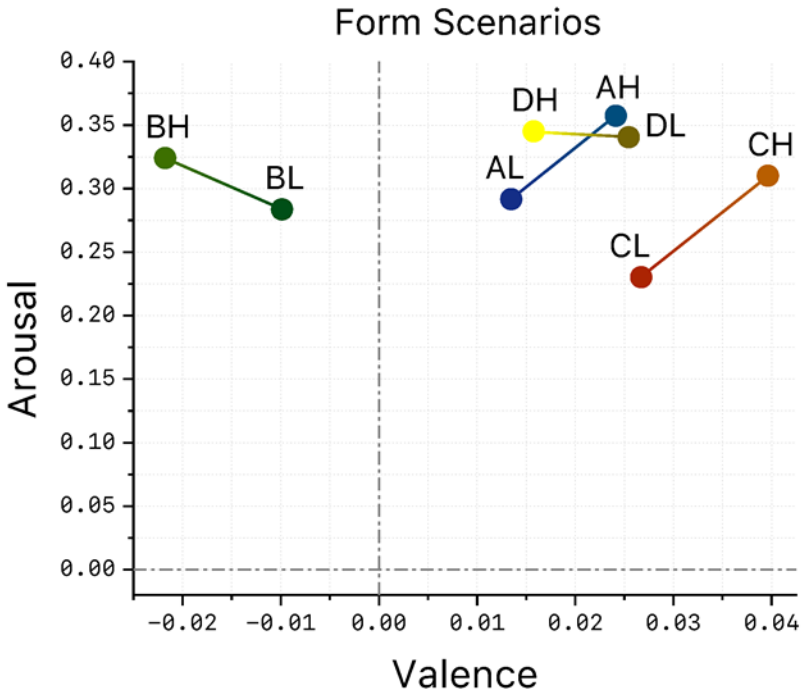


Figure 47: Form scenarios stimulus circumplex model of affect

Implementing randomization of the pair order for the form scenarios did suggest possible mitigation of emotions related to relaxation and boredom created as a result of prolonged exposure to stimuli can assist in eliminating outliers.

Finally, our findings obtained through EEG analysis are coherent with those recorded in previous studies using qualitative approaches [308], [311], [312], proving that EEG can provide reliable quantitative information to improve emotional analysis and frame users' feelings and perceptions.

Outcomes from this study illuminate important aspects of approaching emotional interpretation to design development, particularly with the use of EEG with VR.

To ensure that emotional responses to design variations are reflected accurately, we suggest future studies to incorporate a larger special interest group (such as gender expression, age, socioeconomic status, psychomotor and ethnographic diversity), that can further validate the EEG results, as it accurately reflects the demographic diversity of the study population. Lastly, utilization of more immersive VRs such as the CAVE system, validating with systematic comparison and replicating the experiment in real life, can further assist in validating our findings.

5.5 Conclusions

Getting to know the user perceptions of a product can influence the direction of the design and increase the chances of success. As a result, the implications of the emotional analysis within the scope of the product/service design and development have recently been a matter of interest. Traditional methods have commonly used self-assessment metrics that often lead to subjective results. Therefore, this study aimed to explore the interpretation of emotions using a physiological tool, specifically EEG, to investigate whether colors and form variation could elicit an emotional response. To this end, three different Virtual Environments with chromatic variations of lighting and four VEs with different form variations were examined in Virtual Reality. The study employed a portable EEG headset to record the experimental subject data.

The main findings of this study are related to the validation of the EEG as a method for interpreting emotions by endorsing some results obtained in the previous literature based on questionnaires. The results show that the EEG outcomes are coherent with the theory of colors and the nature of preference of

certain geometric forms. Also, we validated that EEG can provide tangible results to support the emotional analysis research field aiming to eliminate personal bias (a consequence of the traditional methods). Similarly, this research presents an example of the application and validation of emotional EEG quantitative indicators in a new field, contributing to fulfilling an existing requirement expressed in previous studies. Our findings demonstrate that users' emotional states may be analyzed and determined using EEG and that it can be used in conjunction with conventional techniques to prevent biases in the results. Also, physiological methods can provide additional information for the product design, enhancing its success possibilities. Finally, VR technologies combined with other experimental tools are a prominent method for product/service design and development.

According to the literature, no previous studies have developed a generally accepted gold standard for analyzing the emotional influence of colors and form variations in VR using EEG. We expect this explorative study can be used as a starting point in interpreting emotions using EEG as a new approach in product design.

Part of this investigation has been published and can be consulted at https://doi.org/10.1007/978-3-031-15928-2_28 [299].

Chapter 6

Characterization of basic emotions through EEG-based indicators and VR affective elicitation.

In recent years, interest in establishing emotional connections between humans and computers and developing solutions to detect and recognize emotions increased significantly. In this context, EEG has been deployed for emotion identification since it is able to record and decode the human brain's electrical activity. This study explores and validates the use of EEG to characterize emotions. To do this, 30 participants were asked to navigate five virtual reality environments (VEs), selected randomly from a set of ten, designed specifically to elicit one emotion among happiness, disgust, fear, anger, and sadness. Two VEs layouts were available for each emotion: indoor and outdoor. The participants' emotional response while navigating the environments was measured in terms of Valence, Arousal, Dominance, and Engagement variations and integrated with the results from a SAM questionnaire. In this way, it was possible to establish that positive emotions usually have a high valence, high engagement, high dominance, and low arousal, while negative emotions have a low valence, low engagement, low dominance, and high arousal. Furthermore, virtual reality (VR) showed to be a valid emotion elicitation method, as emerged from the EEG analysis, finding out that during the emotional activation while navigating the VEs, the most active brain region was the frontal one, along with considerably strong activation of beta and theta rhythms, which means deep focus, increasing cognitive attention, processing, and elaboration of sensory stimuli.

6.1 Introduction

Emotions are complex physiological and psychological processes produced by individuals' perceptions and environmental stimuli. Indeed, they are involved in logical decision-making, perception, human interaction, and human intelligence [329], [330]. In recent years, Affective Computing has emerged as a multidisciplinary sector considering psychology, physiology, computer sciences, and biomedical engineering [331]. For this reason, the study and development of systems and interfaces able to recognize and simulate human emotions are becoming a research priority [331], [332]. In this sense, affective computing can deal with both emotional classification and emotional elicitation, and society would benefit from the application of systems able to identify emotions since they could be implemented in different working environments, such as education, medicine, economy, and workload studies; as well as help to access and detect cognitive disorders [333], anxiety, or stress [334], [335].

Traditionally, self-reports were developed to assess individuals' mental states. The most used is the Self-Assessment-Manikin (SAM) [336]–[338], a picture-oriented instrument (Figure 48) that allows determining emotional states by classifying three dimensions, also known as affective states or emotional indicators, on an image-based scale: Valence, i.e., pleasantness/unpleasantness; Arousal, i.e., how strongly the emotion is felt and dominance, i.e., how much the person feels to be in control of the emotion. Still, self-reports could lead to personal bias, which is detrimental to emotion detection.

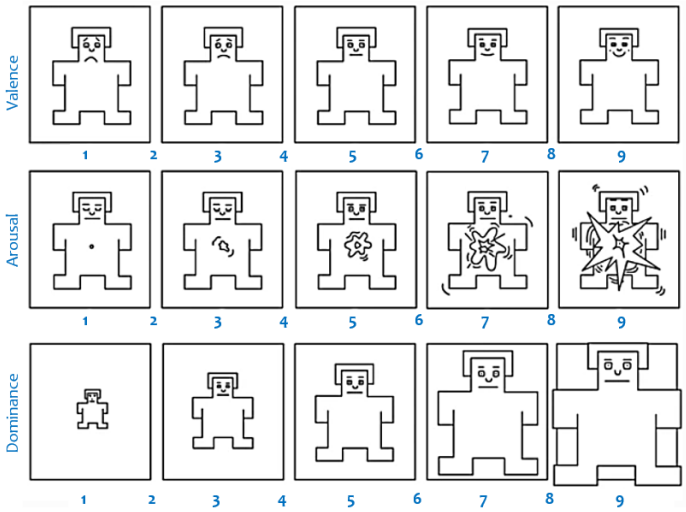


Figure 48: Self-Assessment Manikin

On the other hand, EEG devices allow measuring emotional metrics, such as Valence, Arousal, Dominance, and Engagement, thanks to their relationships with the brain signals (theta (θ), alpha (α), beta (β), gamma (γ) frequency bands), making possible the description of the affective states of an individual [323]. Thus, the use of EEG signals in detecting and classifying emotions, besides being relevant for human-computer interaction [339], [340], provides a more in-depth characterization of the emotional state. Furthermore, emotion investigation has the additional purpose of understanding and profiling the correct stimuli to evoke emotions. One of the most known techniques for emotion elicitation is visual stimulation through images and videos. Therefore, many databases containing images, videos, and audio have been created, such as the International Affective Picture System (IAPS) [341], the Geneva Affective Picture Database (GAPED) [342], and the International Affective Digitized Sounds (IADS) [343].

In this context, virtual environments are gaining ground in creating immersive and interactive experiences due to their suitability to induce more emotional responses than the previously mentioned static approaches [305], [344]. For this reason, this study aims to analyze EEG as a method for emotion characterization and explore how user emotions are influenced by a set of virtual environments designed and validated to induce one specific emotion [312]. The EEG outcomes will be then associated with those obtained from the SAM reports and integrated into a single visual composition. The target emotions are happiness, disgust, fear, sadness, and anger.

This chapter is structured as follows: Section 6.1 presents the background research on the theory of emotion and the emotional indicators. Section 6.2 and 6.3 explains the methodology and experimental setting up. In Section 6.4, the results are discussed, and in Section 6.5, the study's conclusions are reported.

6.1.1 The Basic Emotions theory and the VAD classification Model

Emotions allow us to communicate with others, recognize our emotional states, and express ourselves, depending on the situation. Paul Ekman proposed a "discrete" model based on six basic emotions, universally accepted and comprehensible: happiness, disgust, fear, sadness, anger, and surprise [345]. The theory introduced by Ekman has been used frequently in Facial Expression Recognition since it presents a set of precise facial expressions able to transmit the six primary emotions universally. As previously stated, Russell [309] developed the Circumplex Model

of Affect (Figure 37), a 2D dimensional model describing emotions as functions of two dimensions: Valence and Arousal.

Furthering their studies, Russell and Mehrabian identified a third dimension (Figure 49), Dominance, which indicates individuals' control over a particular situation [346], [347]. In addition, Engagement reflects the users' involvement in an activity and is related to cognitive workload and inclination to perform a task [299], [348]. As previous studies have recommended, accurate structured emotional responses should be described as intensities, such as those used by the VAD (valence, arousal, and dominance) classification model [349] rather than discrete emotional states [350].

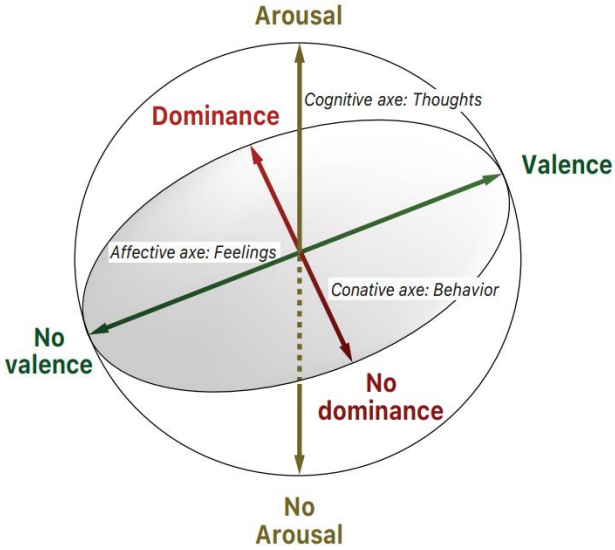


Figure 49: VAD model

6.1.2 Association between emotions and brain signals

With the development of machine learning algorithms and Affective Computing, some studies have tried to establish a correlation between emotions and the Spectral Power Density of brain signals. Other features have been studied, such as Empirical Wavelet Transform (EWT), Event-Related Potential (ERPs), event-related synchronization and steady-state visually evoked potentials, and frontal EEG asymmetry [351]–[353].

In a study regarding changes in regional brain activity, Ekman and Davidson found that positive emotions produce an activation of the brain's left frontal asymmetry [354]. Moreover, Davidson studied that the change in the alpha (α)

power corresponds to a relative right frontal activation for negative emotions (fear, disgust, and sadness), while a relatively greater activation of the left frontal area is related to positive emotions (joy, happiness) [355]. These observations resulted in what Davidson called “Hemispheric lateralization”, which states that the left frontal brain hemisphere activation is correlated with approach motivation, and in contrast, the right frontal with avoidance motivation [356].

Recent studies have shown that a decrease in the frontal brain’s activity occurs in people feeling scared [357]. Another study showed that disliking classical music corresponds to low valence and high arousal, and a higher right frontal activation. On the other hand, enjoying classical music is related to high valence, low arousal, and a higher left frontal activation, suggesting an asymmetric frontal activation when considering the alpha (α) band [358]. On the opposite, beta (β) waves result in being more active in the frontal cortex during intense, focused mental activity [288]. Other studies showed that alpha (α) and theta (θ) bands are related to emotional states [359]–[361] and can be used as indicators of cognitive workload. They are known to be associated with a variety of mental states since alpha (α) brain patterns are related to relaxation, while theta (θ) ones are commonly associated with drowsiness and deeply meditative conditions.

The study of theta (θ) rhythm is still a matter of research; in fact, studies have found that an increase in cognitive effort is characterized by a higher theta (θ) power and lower alpha (α) power, while the opposite happens during rest [334]. Also, higher theta (θ) activity can be associated with higher levels of task difficulty and complexity in the frontal area [348]. Theta (θ) has been related to inward-focused mental tasks, implicit learning, daydreaming and fantasizing [362]; it has also been found to be associated with exploring unfamiliar environments [363]. Recently, a new study [364] found that theta (θ) rhythm is greatly amplified during VR applications, which implies promising research opportunities due to the theta's role in neuroplasticity and memory [365].

Alpha (α) waves are predominant in the frontal and occipital area, theta (θ) waves in the frontal area, beta (β) waves in the frontal and parietal, but also in the occipital and temporal ones, and gamma (γ) waves in the temporal and occipital areas [323], [366]. Figure 50 summarizes graphically the most common correlations between the brain lobes and brain waves related to emotions found in the literature.

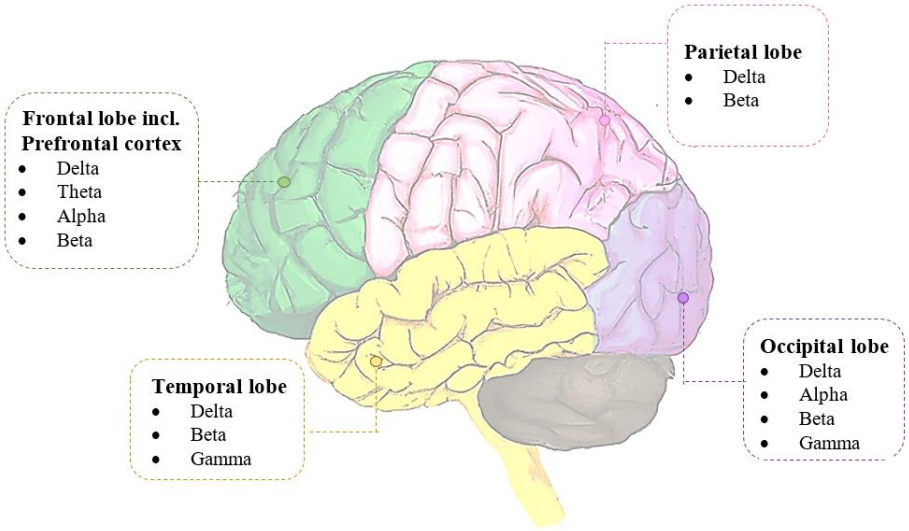


Figure 50: Association of brain waves with brain lobes

Moreover, gamma (γ), the highest in frequency, corresponds to high mental activity and is linked to perception and consciousness. Gamma (γ) frequencies are associated with positive feelings and arousal increments during high-intensity visual stimuli [360], [367], [368], while Beta (β) waves are often related to self-induced positive and negative emotions. Few studies were found on delta waves, mainly associated with deep sleep.

Due to the implications and prospects of emotional research through the association between brain signals and emotional states, this study aims to contribute to the evaluation of emotions using not only self-reports but also EEG by analyzing both emotional responses classified in terms of SAM and in terms of variation of the affective indicators.

6.1.3 EEG-Based Affective Indicators

A state-of-the-art analysis was conducted to identify the emotional indicators and their association with the brain signals. The research was conducted using Scopus and Google Scholar databases. First, the following search terms were applied: “EEG” OR “electroencephalography”, “basic”, “emotions”, “Ekman”, “brain waves”, “happiness”, “surprise”, “disgust”, “fear”, “anger”, “sadness”, “index”, “indicator” and specific indicator names, i.e., “valence”, “arousal”, “dominance”, “engagement”. The search was initially restricted to articles published from 2015 to 2022. Still, since the results were not satisfactory, the time span was extended, and articles from the early 2000 and from the 90s were also considered. Articles

related to engineering, neuroscience, psychology, virtual reality, and marketing were analyzed. The final number of considered articles was 56, carefully selected to meet our eligibility standards. We looked for the following characteristics: English language articles; experimental articles with human subjects; EEG theory and analysis; brain waves delta (δ), theta (θ), alpha (α), beta (β), gamma (γ); articles with basic emotions; articles citing Ekman; Russell's circumplex model of affect; articles trying to establish a relationship between brain waves, basic emotions and emotions indices, i.e., Arousal, Valence, Dominance, Engagement; Content from reference books, conference publications, and textbooks. Articles with the following characteristics were excluded: too specific medical articles; studies using EEG with other neuroimaging techniques.

After this selection, a number of emotional indicators have been found to be associated with emotional states. Furthermore, they can be helpful in better comprehending mental states. As previously stated, the most known indices are Valence, Arousal, Engagement, and, more recently, Dominance.

6.1.3.1 Valence

In particular, valence is known to be an indicator of the pleasantness or unpleasantness of the perceived stimulus; the higher it is, the more positive the emotion; otherwise, the emotion is considered negative. Researchers have found that, according to the International 10-20 System (Figure 38), the most analyzed sensors for the definition of valence are in positions F3 and F4 (frontal electrodes). They are both located in the prefrontal cortex, which is known to play a central role in emotion regulation. In addition, the main activity of alpha (α) has been registered on F3 and F4 [286]. From these observations, valence can be estimated as an indicator of motivational direction by computing and comparing the hemispherical activation between the logarithmic band power of alpha (α) and beta (β) ratio in F3 and F4 (Equation 8) [287], [288], [369]:

$$Valence = \frac{\alpha F4}{\beta F4} - \frac{\alpha F3}{\beta F3} \tag{8}$$

Other studies focused on frontal asymmetry as an expression of emotional states [360] and detected activity mainly in the alpha (α) band. Therefore, the change in the alpha (α) power corresponds to a relative right frontal activation for negative emotions (fear, disgust, and sadness). In contrast, relatively greater activation of the left frontal area is associated with positive emotions [355]. Thus, as stated in the previous chapter (Equation 7), valence has been as well studied by

subtracting the natural logarithm of the left hemisphere alpha power (αF3) from the natural logarithm of the right hemisphere alpha power (αF4) and comparing their difference [286], [299], [348], [370].

$$Valence = \alpha F4 - \alpha F3 \tag{7}$$

In literature, other Valence equations have been proposed. Equation 9 measures valence as the difference between the power ratios of beta/alpha measured in prefrontal and frontal electrodes AF3, AF4, F3, and F4 [348]:

$$Valence = \frac{\beta(AF3, F3)}{\alpha(AF3, F3)} - \frac{\beta(AF4, F4)}{\alpha(AF4, F4)} \tag{9}$$

6.1.3.2 Arousal

Arousal expresses the intensity of the emotion. It can also be described as the psychological and physiological state of being proactive (activation) or reactive (deactivation) to some stimuli. Since alpha (α) waves are associated with states of relaxation and beta (β) waves with states of alertness, researchers have established that these waves are correlated through an inverse relationship. In addition, a link was found between brain inactivation and alpha (α) activity. This suggests that the ratio beta/alpha can express a person's arousal state. In Equation 10, the arousal is expressed as the ratio between beta/alpha concerning electrodes AF3, AF4, F3, and F4 [370]:

$$Arousal = \frac{\beta F3 + \beta F4 + \beta AF3 + \beta AF4}{\alpha F3 + \alpha F4 + \alpha AF3 + \alpha AF4} \tag{10}$$

Likewise, as described in the preceding chapter (Equation 6), Arousal can also be expressed in terms of power measured in F3 and F4 [287], [299]:

$$Arousal = \frac{\beta F3 + \beta F4}{\alpha F3 + \alpha F4} \tag{6}$$

Equation 6 is the most frequently adopted in the literature; it was therefore preferred for this study.

6.1.3.3 Dominance

Dominance addresses people's control over a circumstance, including their emotional state [371]. Russell and Mehrabian introduced a three-dimensional description of emotions by adding dominance to distinguish between emotions with the same valence and arousal levels. For example, anger and fear can be confused

but differ in dominance: anger usually has a high level of dominance, while fear has a low dominance level. Even happiness and surprise can be misunderstood, but the former is characterized by higher dominance, while lower levels are associated with the latter. In the literature, few studies investigate dominance level detection from EEG signals. Yet, some of them establish that dominance is characterized by an increase in the frontal lobe's beta/alpha activity ratio, plus an increase in beta (β) activity at the parietal lobe [288], [372]. It has been found that the beta/alpha ratio computed on FC6 and F8 can be used to determine the dominance level (Equation 11) [372]:

$$Dominance = \frac{\beta FC6 + \beta F8}{\alpha FC6 + \alpha F8} \tag{11}$$

6.1.3.4 Engagement

Engagement is experienced as attentiveness and measures immersion in a task or activity. It is characterized by increased physiological arousal and beta (β) waves, along with attenuated alpha (α) waves [299]. Thus, it can reflect a person's process of information gathering, visual scanning, and sustained attention [348]. In particular, it is characterized by an increase in the beta (β) activity when the engagement and alertness increase and by a decrease in the alpha (α) and theta (θ) activity, which are assumed to reflect less alertness and decreased task engagement (Equation 2).

$$Engagement\ Index = \frac{\beta}{\alpha + \theta} \tag{2}$$

The EEG-Based engagement index is likely the most employed affective indicator in literature [13], [99], [373]–[376]. Generally, the measurements are made considering all available sensors.

A summary of the most relevant equations found in the literature is reported in Table 33.

Table 33: EEG-Based Affective Indicators

Affective Indicator	Equation	Ref.
Valence	$\frac{\alpha F4}{\beta F4} - \frac{\alpha F3}{\beta F3}$	[287], [288], [369]

Valence	$\alpha F4 - \alpha F3$	[286], [299], [348], [370]
Valence	$\frac{\beta(AF3,F3)}{\alpha(AF3,F3)} - \frac{\beta(AF4,F4)}{\alpha(AF4,F4)}$	[348]
Arousal	$\frac{\beta F3 + \beta F4 + \beta AF3 + \beta AF4}{\alpha F3 + \alpha F4 + \alpha AF3 + \alpha AF4}$	[370]
Arousal	$\frac{\beta F3 + \beta F4}{\alpha F3 + \alpha F4}$	[287], [299]
Dominance	$\frac{\beta FC6 + \beta F8}{\alpha FC6 + \alpha F8}$	[372]
Engagement	$\frac{\beta}{\alpha + \theta}$	[13], [99], [373]–[376]

6.2 Methods and Tools

It is known that the human brain is a complex organ composed of billions of neurons, which communicate with each other through electrical signals. The electrical current generates wave patterns, better known as “brain signals”. These brain signals are classified according to their frequencies measured in Hertz (Hz): delta (δ: 0.5–4 Hz), theta (θ) (4–8 Hz), alpha (α) (8-12 Hz), beta (β) (12-25 Hz), and gamma (γ) (25-45 Hz). Moreover, the brain signals are biomarkers of the perceived emotions in response to certain perceived stimuli, which suggests the possibility of using EEG to acquire natural brain activity [299], [323], [377], [378].

Each type of band can be associated with certain states of mind [348], [379]. The theta (θ) band is related to drowsiness and lower mental activity. The alpha (α) band is associated with relaxation and sometimes with focusing attention. The beta (β) waves are linked to alertness and active concentration. The gamma (γ) waves correspond to perception and consciousness.

Following the previous chapters' methodology, this study was conducted using a mobile EEG headset composed of 14 saline electrodes positioned according to the International 10-20 System. The sensors are placed in AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2 and two additional CMS/DRL reference channels

at P3 and P4. An even number means the electrodes are in the right brain hemisphere, and an odd number indicates a placement in the left hemisphere.

To evaluate the affective indicators (Valence, Arousal, Dominance, Engagement), Equations 2, 6, 7, and 11 were selected after checking their frequency of use in the literature. The EEG activity was recorded for 60 seconds at a sampling rate of 128 Hz. A bandpass filter and FFT were performed for data analysis and feature extraction, and a Hanning window was applied to reduce noise. The squared magnitude of the complex FFT value was averaged in each frequency band. The band power (μV^2) was computed every 8 Hz, and only "artifact-free" signals were considered during the experimental phase.

Similarly to previous studies, this methodology adopted a within-subject design experiment, meaning that independent acquisitions are performed for each subject. Then, the EEG measurement was divided into two phases: the EEG baseline and the EEG activity while carrying out the task (Figure 29). The difference between these two recordings was considered for the analysis [299], [324].

6.3 Experiment Setup

In recent years, VR has been widely used as an emotion elicitation technique by creating multisensorial and interactive environments [305], [312], [380]. For this reason, ten validated VEs were considered in this study to create an immersive experience for the participants.

Specifically, the VEs were composed of certain elements more likely to elicit a specific emotion: happiness, disgust, fear, sadness, or anger. For each considered emotion, two VEs were designed: 'indoor' and 'outdoor' [305], [312], [380].

Following there is a brief description of the selected VEs:

- *Outdoor Happiness* (OH). This VE was created to represent a beautiful tropical beach, open and expansive, conveying a sense of vastness. Set during sunny daytime, almost sunset, the colors were warm so that a feeling of relaxation could be felt. The sound of waves characterized the background music. Figure 51a.

- *Indoor Happiness* (IH). In this case, the VE was a playful, colorful, and almost magical world. A starry sky decorated the room, and some festive and bright lights lit it. The whole scenario was characterized by different

sounds: the animals and the objects moving, but also the background music, which was an electronic psychedelic melody. Figure 51b.

- *Outdoor Disgust* (OD). This VE consisted of a dirty picnic scene, full of dirty tables, cockroaches, and trash all over the place. There were dirty bathrooms along the path, and a person inside was audibly vomiting. Figure 51c.

- *Indoor Disgust* (ID). A dark grey room was designed, representing a dirty public latrine full of excrement and insects. Figure 51d.

- *Outdoor Fear* (OF). A dark and gloomy forest was realized for this VE, characterized by many startling elements such as crows, red eyes peeking in the dark, dead bodies, and zombies. Figure 51e.

- *Indoor Fear* (IF). The VE was set in a haunted house, entirely in the dark, where the only light source was the beam of a torch. There were many frightening elements, such as a monster appearing suddenly, a doll, creepy music, and evil laughers. Figure 51f.

- *Outdoor Sadness* (OS). A desolate and polluted city was represented, where a nuclear disaster happened, and no person was around. Figure 51g.

- *Indoor Sadness* (IS). The VE represented a hospital waiting room in dark grey color, where there were visibly and audibly people in pain. Figure 51h.

- *Outdoor Anger* (OA). A maze with no exit composed the VE, characterized by the presence of some holes, causing the participant to get back to the starting point. A timer was added to elicit anxiety and frustration for the impossibility of reaching the end. Figure 51i.

- *Indoor Anger* (IA). A school on fire was simulated, where no person was in sight, but screams and sirens of the ambulance could be heard. A timer was added to emphasize the difficulty of reaching the end before getting in danger. Figure 51j.

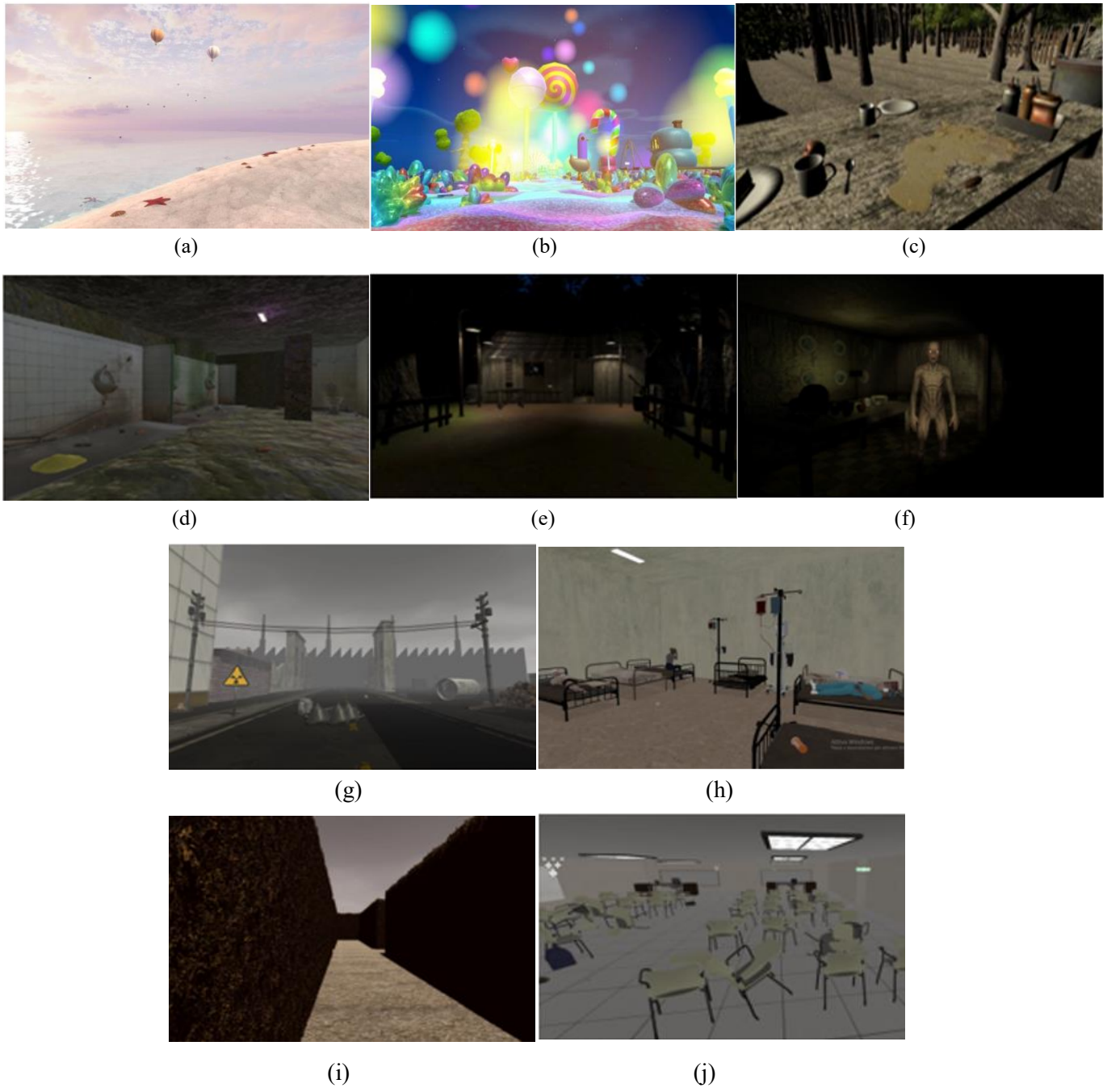


Figure 51. Screenshots of the selected VEs. (a) Outdoor Happiness OH. (b) Indoor Happiness (IH). (c) Outdoor Disgust (OD). (d) Indoor Disgust (ID). (e) Outdoor Fear (OF). (f) Indoor Fear (IF). (g) Outdoor Sadness (OS). (h) Indoor Sadness (IS). (i) Outdoor Anger (OA). (j) Indoor Anger (IA).

A total number of 30 persons aged between 19 and 36 were involved in a controlled experiment. All participants were informed about the research, the protection, and the use of their data, and all of them signed an informed consent. Then, each person at a time sat in an adjustable chair in front of a 27-inch monitor equipped with a mouse, a keyboard, and an external speaker. Before starting the experiment, the EEG headset was set up, and the initial baseline was measured. Each user was asked to explore five VEs, selected casually from the total set of ten, one for each emotion. While visiting the VE, the participants' brain activity was measured with the EEG headset. The experimental flow can be seen in Figure 52.

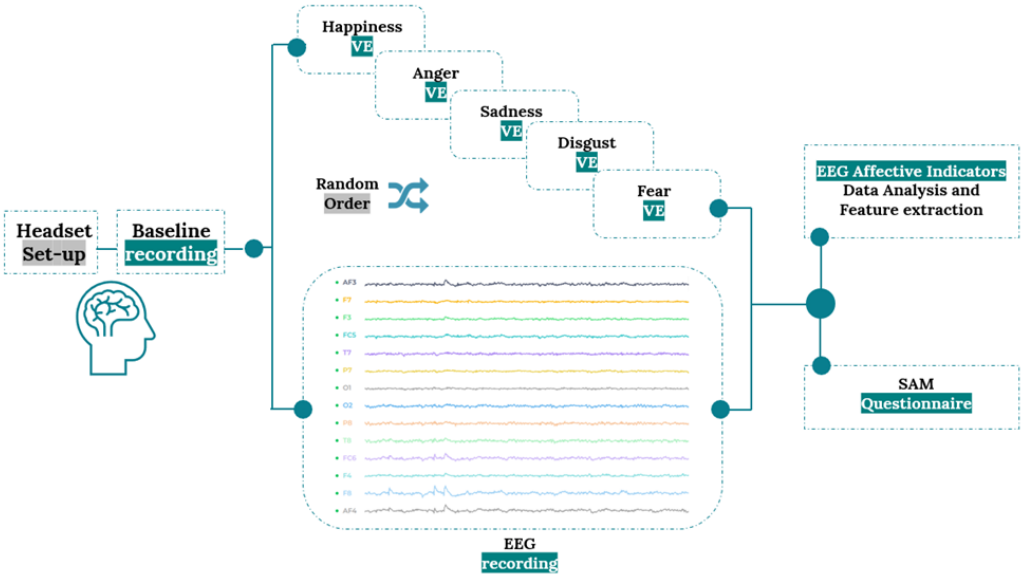


Figure 52: Experiment Procedure

6.4 Results

At the end of each visit, the participants were asked to answer a SAM questionnaire and rate Valence, Arousal, and Dominance.

The EEG data was then processed, and the found artifacts were removed. A total of 27 data-set free of artifacts were considered. Then, Valence, Arousal, Dominance, and Engagement were extrapolated from the EEG data for each VE. The baseline data was subtracted from the post-stimulus response to analyze the VE stimuli' contribution to the emotional state. The median was analyzed to determine the central tendency of the dataset. In addition, measuring the power spectral density (PSD) of the brain signals alpha (α), beta (β), theta (θ), and gamma (γ) at

each sensor's location made it possible to determine the most active brain areas for each brain wave.

6.4.1 EEG brain activity and VAD+E activation responses

By analyzing the stimuli response in terms of Valence, Arousal, Dominance, and Engagement (VAD+E) in each VE, it was possible to find similar features. Firstly, arousal was characterized by a median positive variation for every environment. This confirms that the participants were awake and aware of the task they were carrying out. By looking more specifically at its behavior over time, negative peaks could be interpreted as moments where the arousal decreased because of mental fatigue, rest and/or less exciting situations.

The highest arousal was found in the Outdoor and Indoor Disgust VEs, and Indoor Fear VE; this last, in particular, reported the highest arousal value from all the scenarios, reflecting the expected stimuli intensity. The lowest arousal was found instead in both Indoor and Outdoor Sadness.

Regarding dominance, it presented a median positive variation in every scenario. Thus, the participants felt in control of the situation since they were still experiencing a VR in a controlled context. The highest dominance was found in the Indoor Fear VE, which, combined with its valence, reflects a high emotion intensity with an elevated feeling of control; this is notable since the participants probably tended to unconsciously raise their sense of control to overcome the fearful stimuli. Similar but opposite behavior was evidenced in Indoor Happiness, which had the lowest dominance of all the VEs; this VE, intended to elicit joyfulness, generated in the participants a sense of being in control of the situation. On the contrary, Open Happiness, the tropical beach, caused a higher dominance, as expected.

By looking at the specific details of the temporal trend, the environments eliciting negative emotions presented more negative peaks, indicating that the participant felt less in control of the experience on several occasions. During Sadness VEs, the dominance was positive and constant; this could be explained since these environments were not designed to elicit despair, which is a less controllable emotion. The median values of the affective indicators are reported in Figure 53.

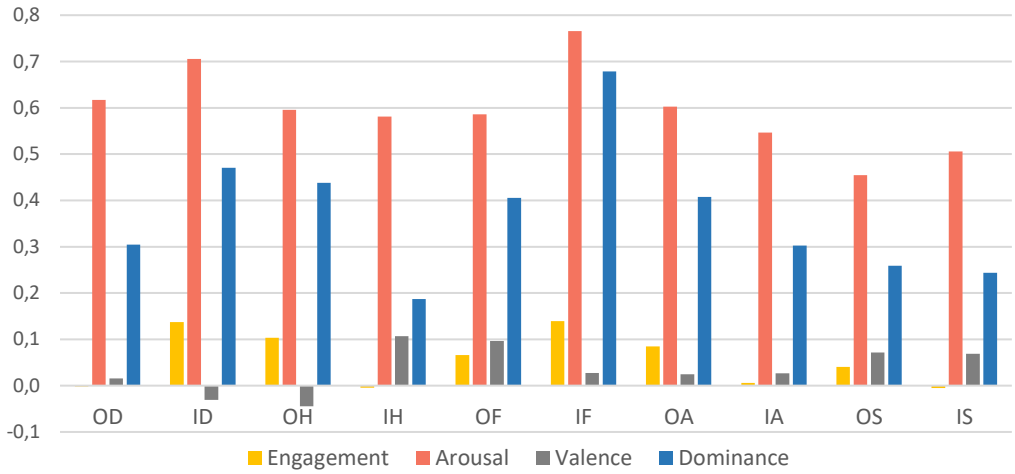


Figure 53: VEs Affective Indicators

The median trend of valence was positive for almost all the VEs. With the few exceptions of Indoor Disgust and Open Happiness. In the first case, the stimuli were designed to elicit negative emotions, which corresponds with the results. In the case of OH, the low valence, in combination with a positive dominance, could be due to the presence of the elements related to quietness and serenity, which ultimately led to a decrease in interest. Quite the opposite, the highest Valence value was found during Indoor Happiness, as was expected.

These behaviors suggest that the emotions were felt and classified as pleasant or unpleasant, but with possible external factors altering this mental association, such as tiredness, length of the experiment, or some elements that were not perceived as pleasant/unpleasant. As in the cases of both Sadness VE and Outdoor Fear, which resulted in a positive valence, one potential hypothesis is that some people experience a sense of pleasure and fun when visiting horror houses and thrilling experiences due to a phenomenon known as “positive arousal.” Positive arousal results from an individual’s ability to respond to a “frightening” stimulus in a manner that is pleasurable. In other words, some individuals may find the thrill and sense of danger that comes with these experiences to be exciting and enjoyable.

In most cases, engagement resulted in a positive variation in all environments. Also, when the dominance was higher, so was the engagement, and vice versa. By analyzing the temporal behavior and as demonstrated by the previous experiment in chapter 5, the engagement increased in the initial part of the experiment since there was curiosity and interest but then decreased at the end of it, probably because participants became more accustomed to the VEs.

Moreover, the engagement was helpful in better identifying the emotional state of the participants in those environments where the valence seemed to be invariant concerning the baseline (Outdoor Disgust and Indoor Anger). In fact, the lower the engagement, the less favorable the emotion, and correspondingly valence was lower.

6.4.2 SAM responses and VAD+E characterization

The overall SAM score, and the emotional response in terms of Valence, Arousal, Dominance, and Engagement for each VE, are gathered together in a "semaphore" scheme. This graphical representation offers the general emotional state for each VR environment, as can be observed in Figure 55.

For each one of the VEs, there is one resulting semaphore; in the upper section of the schemes, there are the SAM results (VAD); in the lower section, the EEG-based affective indicators outcomes (VAD+E), and at the right upper corner a digital art representation (Figure 54) of the resulting detected emotion.



Figure 54: Analyzed Basic Emotions. This image was created with the assistance of DALL·E 2

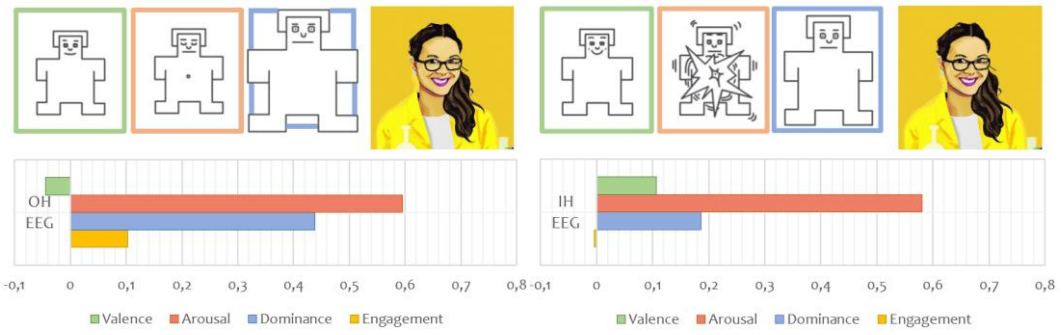
The results revealed that valence was classified as medium-low in Outdoor and Indoor Disgust, Outdoor and Indoor Anger, Outdoor and Indoor Sadness, and Outdoor Fear, as expected since they are all negative emotions. Similar to the EEG results, the valence of Indoor Fear was curiously high, probably because many people found the haunted houses entertaining [312], [380]. Valence was high for Outdoor and Indoor Happiness.

Additionally, arousal was labeled as medium-low in Outdoor and Indoor Disgust, Outdoor Happiness, and Outdoor and Indoor Sadness. It could be interpreted as a non-intensive perception of the emotion. For instance, Outdoor Happiness was expected to have low arousal since the VE was calm and relaxing. This result and the EEG outcome are coherent since the EEG valence for OH was actually low. Conversely, the SAMs of Indoor Happiness, Outdoor and Indoor Fear,

and, Outdoor and Indoor Anger were medium-high, indicating that the intensity of the felt emotions was elevated.

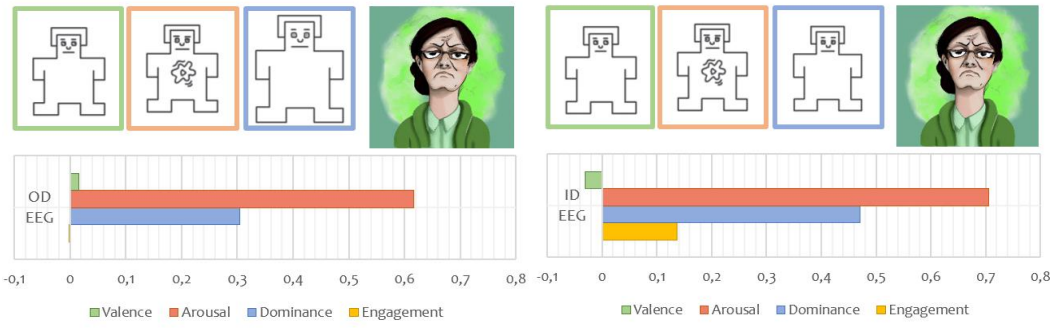
Regarding dominance, it was labeled as medium-low in Indoor Disgust, Outdoor and Indoor Fear, and Outdoor and Indoor Anger, as expected since these environments were designed to not allow the participants to stay in control of the situation. Surprisingly, Outdoor Disgust was characterized by a high dominance, probably because people found an open forest less disgusting than a dirty indoor place [312], [380]. Outdoor Happiness and Indoor Happiness reported a high dominance, as expected.

The high values of SAMs of Outdoor and Indoor Sadness, along with the EEG results, could be explained, considering that sadness does not involve despair as well [381]. Lastly, according to the overall results of the SAM and EEG-based indicators, we can conclude that the most rated emotion for each Virtual Environment was, in fact, the expected one.



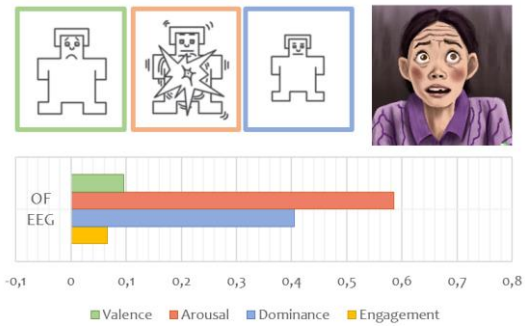
(a) Outdoor Happiness

(b) Indoor Happiness

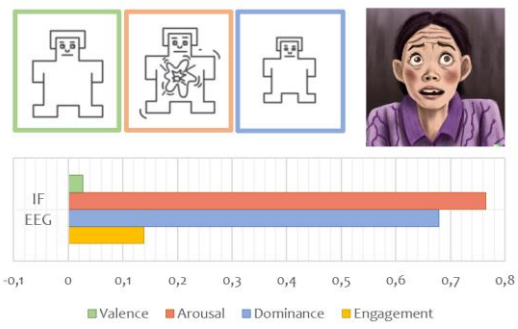


(c) Outdoor Disgust

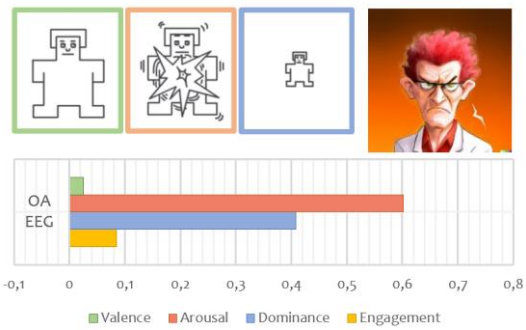
(d) Indoor Disgust



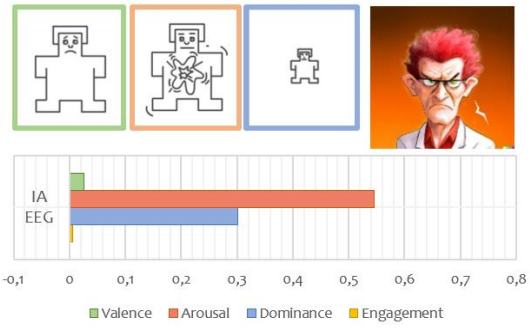
(e) Outdoor Fear



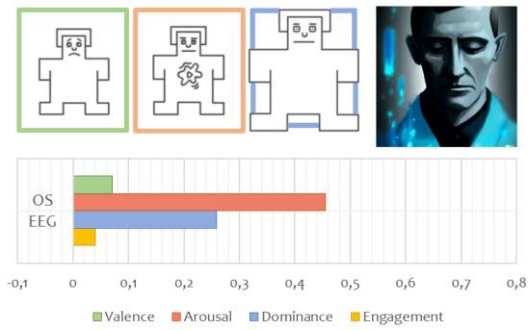
(f) Indoor Fear



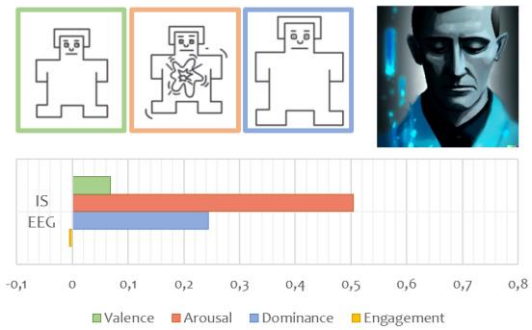
(g) Outdoor Anger



(h) Indoor Anger



(i) Outdoor Sadness

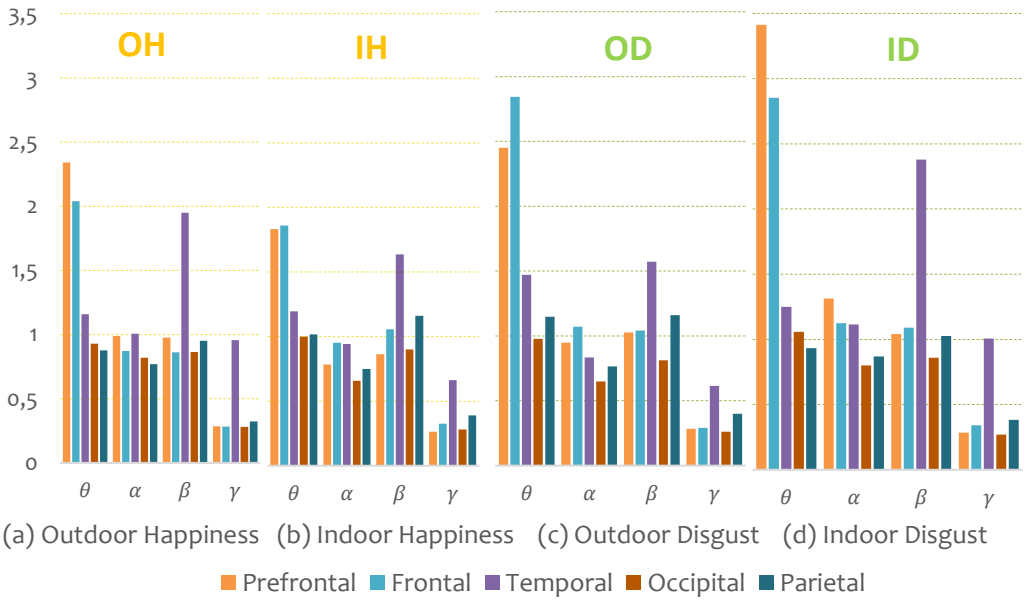


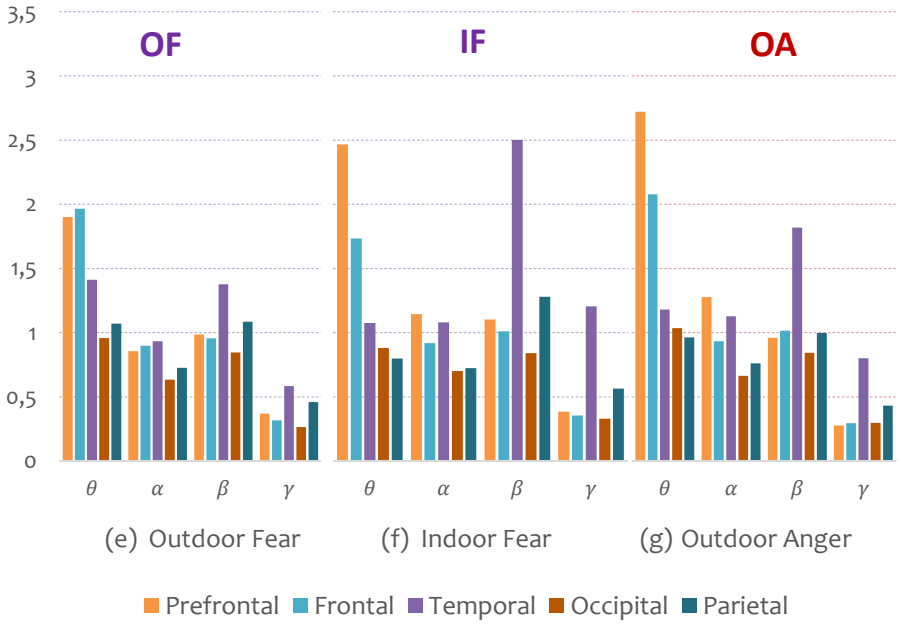
(j) Indoor Sadness

Figure 55: Overall SAM and EEG-Affective Indicators Outcomes. (a) Outdoor Happiness OH. (b) Indoor Happiness (IH). (c) Outdoor Disgust (OD). (d) Indoor Disgust (ID). (e) Outdoor Fear (OF). (f) Indoor Fear (IF). (g) Outdoor Anger (OA). (h) Indoor Anger (IA). (i) Outdoor Sadness (OS). (i). Indoor Sadness (IS).

Regarding the brain areas activation (Figure 56), the most active one for all scenarios was the frontal, particularly for theta (θ), alpha (α), and beta (β), while

for gamma (γ) was either frontal or temporal (OH, IH, ID, IF). These results were expected because the brain signals have been associated with the most active brain areas during emotion perception [367].





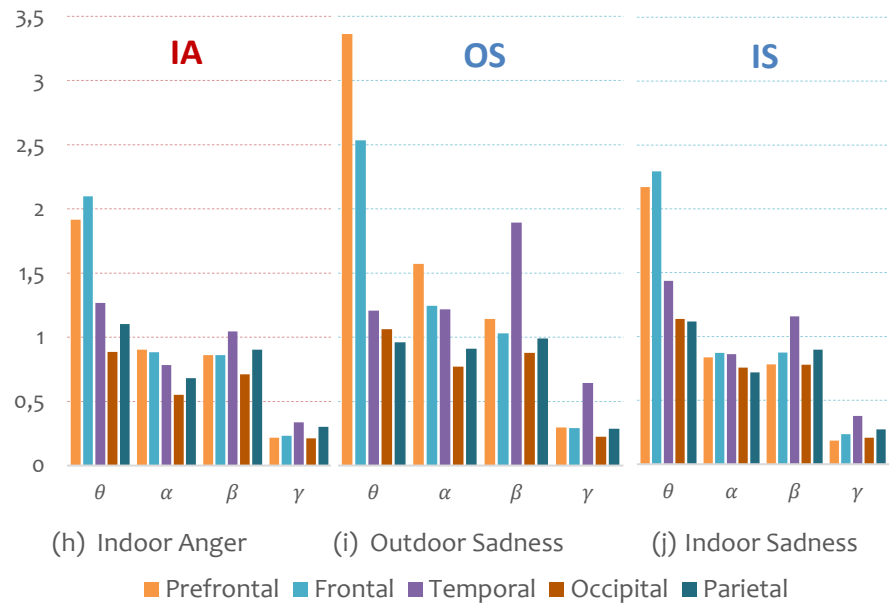


Figure 56: PSD (μV²) vs. Brain Area Activation. (a) Outdoor Happiness, (b) Indoor Happiness, (c) Outdoor Disgust, (d) Indoor Disgust, Outdoor Fear (e), Indoor Fear (f), Outdoor Anger (g), Indoor Anger (h), Outdoor Sadness (i), and Indoor Sadness (j). Considered frequency bands: θ (4-8Hz), α (8-12Hz), β (12-25Hz) and γ (25-45Hz).

Beta (β) PSD increased noticeably mostly in temporal and parietal sensors, but also in the occipital ones. It is known that beta (β) is associated with alertness and concentration [348], [379] and is predominantly active in the frontal region but also in the temporal, parietal, and occipital lobes, whose primary functions are the procession of auditory and visual stimuli and the formation of memory [367]. Thus, the participants were paying attention to what they were doing and collecting sensory information.

For all the scenarios, the highest measured PSD in all locations was theta (θ). As theta (θ) is associated with daydreaming mental states [377], [379], a high activation can be detected since the participants were mindful and navigating imaginary worlds. In detail, theta (θ) PSD was the highest at frontal sensors, corresponding to increasing cognitive attention in the frontal area [334], [348].

The overall sensors' activation in terms of PSD of the brain frequencies is presented in Figure 57. The results made evident the strong activation of theta (θ) rhythms in all the VEs, which is a coherent result according to the recent findings of Safaryan and Mehta [364] regarding the ability of VR to amplify theta (θ) frequencies. This recently discovered VR feature entails a promising outlook in the

field of emotional design, as VR can be used to boost and benefit target neural dynamics. In addition, one of the most effective VE in terms of neural stimuli activation was the Indoor Fear, as it produced the highest gamma (γ) and beta (β) frequencies, reflecting alertness and a high level of focus.

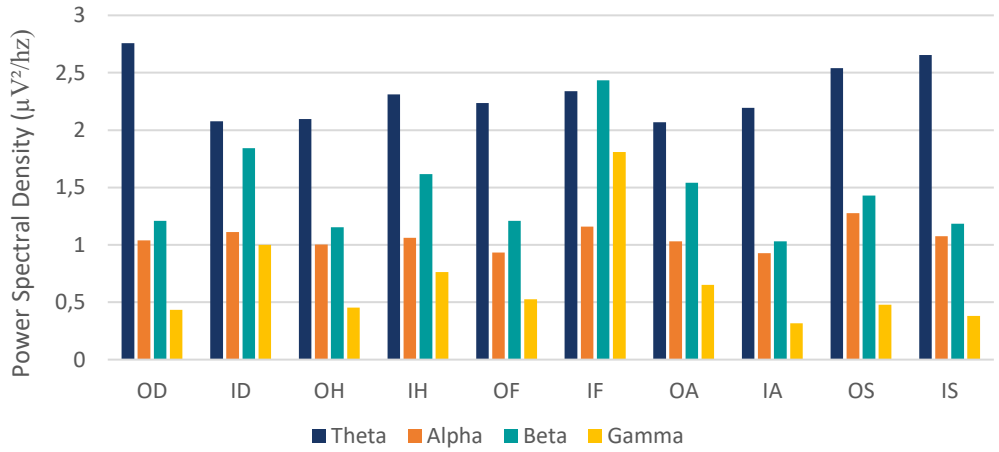


Figure 57: VEs Frequency Bands Activation

6.5 Conclusions

EEG-based Emotion Recognition is becoming crucial for developing machines to be integrated for the benefit and application in society. In fact, it could be helpful in education to observe students' mental state towards teaching materials, or in medicine to allow doctors to assess their patients' mental states and to get better treatments for their psychological conditions, or more generally to understand a worker mental conditions during ordinary and stressful situations. Besides self-reports, many emotion detection and classification techniques have been analyzed: emotional speech processing, body gesture and movement, multimodal system, and facial expression recognition. In this context, this study aimed to explore the interpretation of emotion using EEG. To do this, an experiment was conducted to investigate the emotional response of participants interacting with VEs, by employing a portable EEG headset to record the subject data during the experiment.

The main findings of this study are rewarding since it was possible to demonstrate a correlation between emotions, EEG signals, and the quantitative emotional indicators (Valence, Arousal, Dominance, and Engagement); moreover, additional evidence was found, suggesting that EEG analysis can be employed to determine users' emotional states, along with other traditional methods, such as the Self-Assessment Manikin. In particular, the semaphore results showed that all the

considered features enabled a comprehensive assessment of the users' emotional state.

Furthermore, it was possible to verify that the EEG was capable of detecting the elicited emotions since the EEG outcomes coincided with the VEs' expected emotions and the SAM's most-rated results. The most stimulating VE was Indoor Fear, reflecting a high activity in Beta and Gamma rhythms and positive valence; this behavior was observed in similar experiments in participants who normally experience enjoyment during fearful situations, as in horror films or video games. On the contrary, the Indoor Anger produced the lowest gamma and beta activity from all the VEs as well as low engagement, due perhaps to its similar and continuous stimuli.

As expected, the most active brain lobe for all the VEs was the frontal one, including the prefrontal cortex, since the frontal lobe is the most involved in emotion perception. The sensors' activation highlighted that the highest measured PSD were those of theta (θ) and beta (β), which means that increasing cognitive attention, processing, and elaboration of sensory stimuli was achieved with the VR. Furthermore, the strong activation of theta frequency is aligned with the recent findings about the capacity of VR to intensify theta rhythm. Our results are promising since the enhancement of theta through dedicated VEs could support the studies on deep relaxation, implicit learning, and inward focusing.

We believe this study can be used as support for developing and validating tools aimed at comprehending human emotions through EEG acquisitions independently or together with other traditional and machine learning approaches. This study considered five basic emotions (happiness, disgust, fear, sadness, anger) as surprise evaluation via VR was non-satisfactory; consequently, the research is still open to exploring the emotional states related to surprise in depth. Moreover, our findings support the theory that Affective Computing and VR help to identify methodologies to discriminate better parameters able to elicit emotional responses.

Chapter 7

Exploring the determinants of Acceptance of an e-Learning Agriculture Platform: Proposal and Validation of a TAM Extension.

UE dimensions encompass users' attitudes and usage behavior toward new systems. Advances in UE tools have been developed not only at the hardware level but also in the research and evolution of novel models and theories that look to explain the determinants of new technologies acceptance. On the other hand, information and communication technologies (ICT) have played a significant role in all aspects of modern society and have impacted socioeconomic development in sectors such as education, administration, business, and agriculture. However, the benefits of such technologies can be appreciated only if users use them. In order to predict and evaluate the adoption of new technological tools, the technology acceptance model (TAM) could be a valid aid. For this purpose, this chapter initially identifies the most commonly used external variables in e-learning, agriculture, and virtual reality applications to then proceed with a further validation in an e-learning tool designed for EU farmers and agricultural entrepreneurs. The analysis shows that computer self-efficacy (SE), individual innovativeness (II), computer anxiety (ANX), perceived enjoyment (PE), social norm (SN), content quality (CQ), experience (EXP), and facilitating conditions (FC) are the most common determinants addressing technology acceptance. Furthermore, findings evidenced that the external variables have a different impact on the two main beliefs of the TAM Model, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). After validation, the results suggest that CQ is the primary determinant of farmers' and agricultural entrepreneurs' perception of the tool's PU. Furthermore, EXP and SE shape potential users' perceptions about PEOU.

This study is expected to bring theoretical support for academics when determining the variables to be included in TAM extensions and to provide empirical evidence of TAM's validity to assess technology acceptance during the design and development of e-learning applications in the farming sector. This work was supported by the European Erasmus+ project “Farmer 4.0”, project number: 2018-1-IT01-KA202-006775.

7.1 Introduction

In the current high-speed connected world, there is a growing awareness of the advantages offered by information and communication technologies (ICT) and their crucial role in fostering human progress, promoting knowledge societies, supporting sustainable development [382], [383], and accelerating economic growth [384]. Hence, integrating ICTs in all aspects of socio-economic agendas has become a cutting-edge challenge [385], and as years go by, billions of dollars are invested in technological initiatives in various development sectors [386]. However, the benefits of such technologies can only be appreciated if people use them [387].

Researchers from different science and technical areas have developed a set of complementary and extended frameworks to predict and evaluate the adoption of new technological tools. The most diffused approach is the TAM, proposed by Davis [388]. This model investigates the drivers of technology acceptance, from the perspective of users' perceptions about innovations and social and contextual factors. The validity of the TAM has been examined in sectors such as food industry [389], wearable technologies [390], health [391], social media [392], electronic commerce [393], energy services [394], financial services [395], among others. Under this model's theoretical and practical logic, we want to measure the potential acceptance of an e-learning tool designed for 29 EU farmers and agricultural entrepreneurs within a European Erasmus + project (FARMER 4.0-Farmer teaching and training laboratories).

The contribution of tools such as FARMER 4.0, should not be overlooked as it helps to the strengthening of two fundamental sectors for sustainable development, namely e-learning and agriculture. As pointed out by Nie et al. [383], the e-learning sector and sustainability are closely related. Online education, aiming to improve the quality of learning programs, promote the acquisition of sustainability-related values and skills, and increase awareness about sustainable development initiatives, can positively affect local and global development.

The e-learning approach adopted by FARMER 4.0 is an innovative alternative to promote the development of new agricultural skills. Supported by the ICTs, online education gives access to up-to-date knowledge without affecting users' daily productive activities [383], [396]–[399], independently of geographical location [400]. From the perspective of sustainable development, e-learning initiatives should promote and improve continuing education, ensure the acquisition of sustainability-related knowledge and skills, and increase public awareness and understanding of sustainable development and its implications [383]. However, the ultimate value that users will obtain from tools like FARMER 4.0, and the achievement of Sustainable Development Goals will depend on the extent to which the target population effectively uses the technology [387].

Despite the increasing use of information systems (IS) in the agricultural sector [401] and the awareness of the benefits of ICTs applications in farming activities [402], previous works have revealed low acceptance and adoption of these technologies among farmers [403]–[406]. For this reason, understanding the aspects that move users to accept or reject these types of technologies is paramount [387].

7.1.1 Problem Formulation

FARMER 4.0 wants to actively contribute to the achievement of the EU priority's objectives, developing a new training model to foster the transfer of skills between “traditional" farmers, technologists, researchers, and agricultural entrepreneurs of the digital age. Thanks to the proposed training, the digital age agricultural entrepreneur (FARMER 4.0) could use the most modern digital manufacturing technologies to create tools, models, and practices that will revolutionize the agricultural sector by taking advantage of digital creativity and interactivity of high-quality solutions. However, in addition to the farmers' concerns regarding the use of new technologies, EU agriculture suffers from delays in keeping up with modern technologies and skills, which would allow a more significant safeguard of the competitive advantage in comparison with non-EU markets. In line with the previous context, we posed the following research question:

- What are the external TAM variables that drive the acceptance of the e-learning tool FARMER 4.0?

To answer this question, in the first part of this study, we identified the most commonly used external determinants in e-learning, agriculture, and VR

applications. We wanted to understand how traditional farmers, people who are used to getting by and who find solutions when problems arise using hands and traditional tools, are ready for new digital technologies. To comprehend the relationships between research topics and TAM variables, Quality Function Deployment (QFD) methodology is used.

After that, on the grounds of the findings obtained, the last research objective was to identify the potential factors behind the adoption of the e-learning tool FARMER 4.0. To this end, we conducted an empirical validation of the TAM initially proposed by Davis [388] and assessed the TAM extension developed for the context of the e-learning tool.

7.1.2 Research Objectives

The present study pursues a fourfold objective: (1) Identify and prioritize the most commonly used external factors affecting the two primary constructs, such as perceived usefulness (PU) and perceived ease of use (PEOU) of the TAM in e-learning, agricultural and virtual reality innovations. Those three sectors are selected based on the innovative tool's nature under analysis. (2) Identify the main research topics addressed in the literature of TAM in e-learning, agriculture, and virtual reality through the application of the QFD as an organizing framework for the literature review. (3) Propose a TAM extension within the context of FARMER 4.0. (4) Validate the TAM extension within the study setting.

The chapter starts with a brief description of the TAM and QFD models in section 7.2 and the proposed research methodology in section 7.3. Then, in section 7.4, we identified the most commonly used external variables in e-learning, agriculture, and VR. In section 7.5, we analyzed thanks to QFD, the most commonly used external variables in the fields of interest that affected PU and PEOU of the TAM and based on the most frequently used external variables, we proposed a TAM extension within the context of the FARMER 4.0 to assess farmers' acceptance. Subsequently, we proceeded to frame the validation of the proposed TAM extension; hence, section 7.6 presents the stated hypothesis and the instrument used to test them, and in section 7.7, the results obtained after constructs and model validation are displayed. Finally, in section 7.8, we summarize the practical implications of our findings, and in section 7.9, conclusions and future directions of investigation are reported.

7.2 Background

The e-learning tool FARMER 4.0 was designed to help farmers and agricultural entrepreneurs to develop the technological skills they need to succeed in the new digital era. Moreover, the learning model built around the learning system seeks to facilitate the transference of traditional farming skills to protect and strengthen the competitive advantage while facing non-EU markets.

Conscious of the variety of action fields in farming activities and aware of the technologies shaping the sector's future, the system proposes an initial assessment of the current knowledge base and then suggests the most convenient learning path (Figure 58). After the initial mapping of the strengths and weaknesses, the training model gives free access to a set of training modules jointly developed through face-to-face interactions and e-learning sessions. The topics covered by the modules include computer-aided technologies, additive Manufacturing-3D Printing, agricultural entrepreneurship, internationalization and sustainability, Social Networking for Global Farm 4.0, and online communication tools and techniques. Experiential learning is also offered through virtual environments (3D models in Virtual Reality laboratories), job shadowing, and inter-generational co-working laboratories known as Fab Labs.

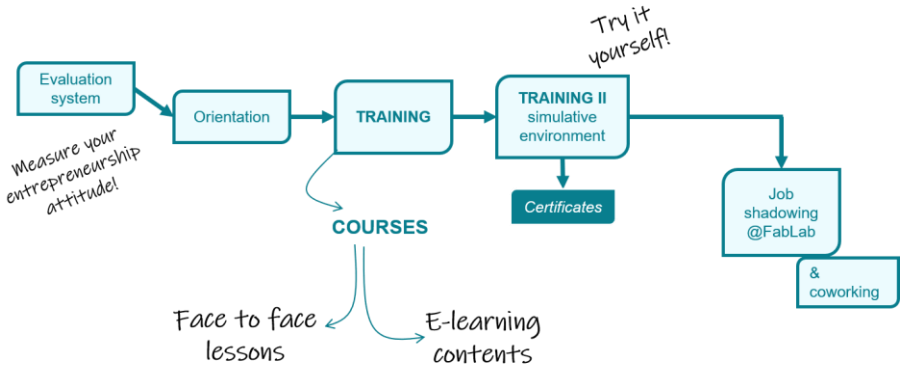


Figure 58: E-learning model FARMER 4.0

Available in five languages, the website (Figure 59) represents a potential facilitator to harness the opportunities offered by modern digital manufacturing technologies helping farmers to create new prototypes, tools, and practices that shape the agricultural sector's future without sacrificing the local capacities and knowledge but rather reinforcing them.



Figure 59: FARMER 4.0 Moodle

7.2.1 The Technology Acceptance Model

In 1985 Fred Davis developed the TAM [388] as a contribution to the field of Management Information Systems (MIS). Since its origin, the model has been a significant step forward in the research area because it enhances the design and development of information systems and represents a practical testing tool to assess systems acceptance in ex-ante use scenarios. Its applicability and validity in a wide range of contexts make it the most utilized theoretical model in Information Systems [395], [401].

To uncover the reasons behind computer-based technology adoption, Davis adapted the Theory of Reasoned Act (TRA) [407] and the Theory of Planned Behavior [408] to the technology context. Under the TRA theory, Ajzen et al. [407] identified two factors that significantly influence the user's intention: the attitude toward the behavior and the subjective norms. On the other hand, in the TPB theory Ajzen [408] stated that, additionally to the factors comprised by the TRA, the adoption of a given behavior is influenced by the ease or difficulty in the implementation. Generally speaking, those two complementary theories formulate that there is a sequence of causal relationships among what individuals believe about using a system and the actual use. The authors state that users' beliefs influence their attitude, which in turn modifies the intention to use or not use a given technology. The intention is the primary determinant of actual use. On this basis, Davis [388] identified two main beliefs, namely Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which are defined as [409]:

- *PU is "The degree to which the person believes that using the particular system would enhance her/his job performance."*

On the other hand,

- *PEOU is "The degree to which the person believes that using the particular system would be free of effort."*

In the initial TAM version, highly influenced by the TRA [410], Davis theorized the existence of a causal relationship between the two main determinants, PU and PEOU, and the Attitude towards use (ATT). The role of Behavioral Intention (BI) was considered in a subsequent TAM version thanks to the contributions of the authors of the TPB. BI was included to represent humans' rational behavior of using the available information to decide whether to do something or refrain themselves. The first modified version of the TAM is shown in Figure 60.

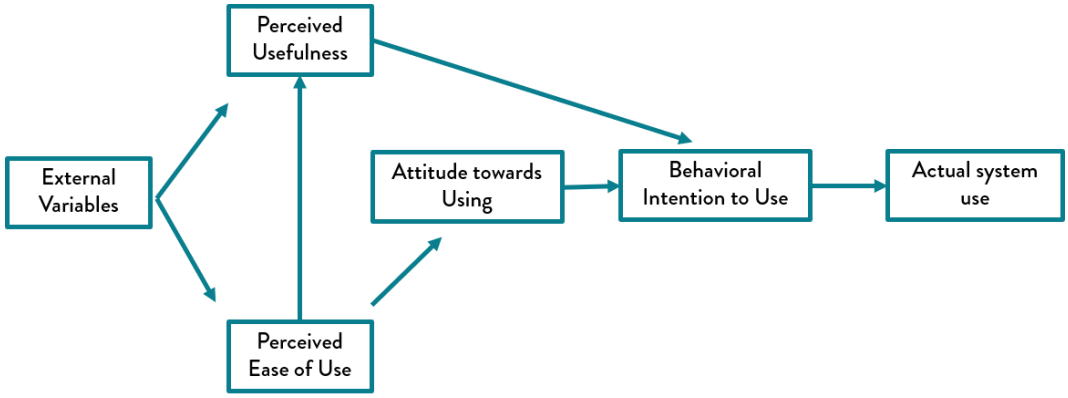


Figure 60: Technology Acceptance Model

As TAM research's body increased, so did the exploration of the social and cognitive processes responsible for PU and PEOU. Subsequent work by Venkatesh and Davis [411] complemented the framework by going further on the analysis of Perceived Usefulness. Their findings suggest that social factors such as social pressure or social norm and image, as well as result-oriented aspects such as job relevance, output quality, and result demonstrability, could have an incidence in the perception of usefulness, mediated in some cases for previous experience with similar technologies. This extended model is known as TAM 2. A third general version, TAM 3, was proposed by Venkatesh and Bala [412]. This version posits computer self-efficacy, external control, anxiety, playfulness, perceived enjoyment,

and usability, as determinants of PEOU. Moreover, TAM 3 provides theoretical support indicating the mutual independence of factors influencing PEOU and those determining PU. Thanks to the flexibility of the TAM, several different extensions have been proposed based on the technology's research objectives, context, and nature. The validity of the TAM has been confirmed not only in information systems applications but also in assessing the adoption of wearable technologies [390], health [391], energy services [394], financial services [395], and e-learning [413], among many others.

According to the TAM [414], the two main determinants, PU and PEOU, are affected by external and context-dependent factors, as shown in Figure 60. In this sense, the TAM's consolidation has been a multi-stage process [415], and multiple extensions have been developed according to the research field. TAM 2 and TAM 3 are the prevailing and more comprehensive extensions. TAM 2 by Venkatesh and Davis [411] focuses on the factors influencing PU and some mediating variables, while TAM 3 unveils the aspects accountable for PEOU [412]. King and He [416] elucidated that there were different types of TAM's applications and classified them in four groups [417] based on whether the analysis focus was: (a) factors predicting PU and PEOU, (b) factors included from other technology acceptance frameworks, (c) variables with potential moderating or controlling effect, and (d) consequent factors which are the attitudes and usage. The present study belongs to the first type.

7.2.2 The Quality Function Deployment

The QFD is a practical customer-driven tool particularly appreciated for product design and development [418]–[420]. This framework was introduced in 1960 by Yoji Akao and appropriated by Mitsubishi in 1972 [421]–[423]. The general purpose of the QFD is to act as a bridge between what customers want (Customer Requirements (CRs)) and the manners in which products or services will respond with their design features (Technical Characteristics (TCs)) to those desires. Therefore, the QFD provides a systematic structure to map user needs and identify and prioritize design parameters to address those needs from an organizational perspective: there will be the assessment of the impact of design characteristics on customer needs, as well as the correlations among design features and the corresponding prioritization [420], [424]–[427].

Many authors have implemented the QFD in their studies addressing the design of products and services with a particular focus on customer experience and

alternative ways to capture user's feedback, as in the works by Iranmanesh et al., Choi et al., Vezzetti et al., Violante et al., Sun et al. [139], [428]–[431].

The reputation of the QFD as a reference framework for design and quality management can be attributable to the multiple advantages it offers. Dolgun and Koksal [427] investigated the main benefits of the framework reported in the literature, and among the most outstanding, they found: (i) improves customer satisfaction by granting users involvement during the design process, (ii) allows a more informed and documented decision-making regarding customer demands and the company possibilities to satisfy them, (iii) strengthens team communication, (iv) reduces time to market and costs by minimizing the risk of errors.

In general, the QFD offers the possibility to systematically identify fundamental aspects in the analysis and depict the variables of interest in the same layout, rank them, and examine the existing relationships. On this basis, we considered the QFD to be the most appropriate framework to give a solid foundation to our study, assuring a user-centered perspective.

7.3 Methodology

For the literature analysis, the study was based on QFD and structured in 3 phases (Figure 61): definition of research categories in TAM, identification of commonly used TAM variables, and analysis of the strength of the relationships represented by the path coefficients.

For the research purposes, we conducted a literature review of theoretical and empirical studies within the last ten years and grouped them into seven categories according to the topic and the research perspective. Papers were selected similarly to the quantitative meta-analysis proposed by Abdullah and Ward [387] and adapted for this study to identify commonly used external factors in TAM extensions in e-learning, agriculture, and VR.

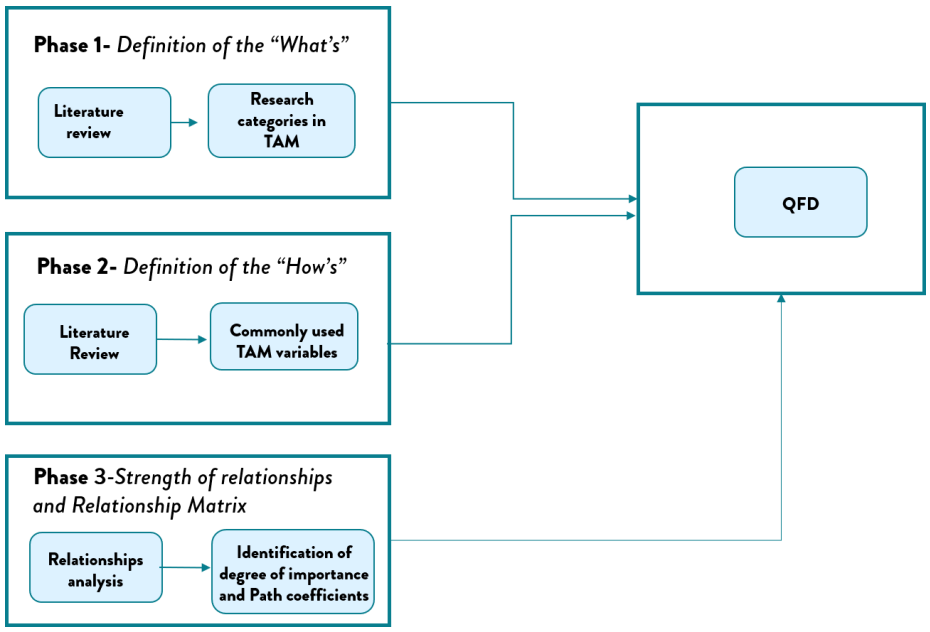


Figure 61: Layout of the proposed methodology

In the third phase, a stricter selection of papers was made in order to analyze the degree of importance of the research categories (What's) and the strength of the relationships between commonly used TAM variables (How's) and the two main constructs of TAM, PU, and PEOU. The degree of importance is represented by the number of works belonging to each research category. The strength of the relationships between most common external variables and PU and PEOU is represented by the path coefficient. Therefore, only studies reporting the path coefficients were considered. Finally, we gathered the previous information to construct the QFD matrix proposed in Figure 62. The papers' selection and classification process are explained in detail in Figure 63.

The validation of the TAM extension in the context of FARMER 4.0 followed a quantitative method. Further details concerning the model to be validated, the associated research hypothesis, the questionnaire, and the data collection and construct validation processes will be presented in the validation subsection (section 7.6).

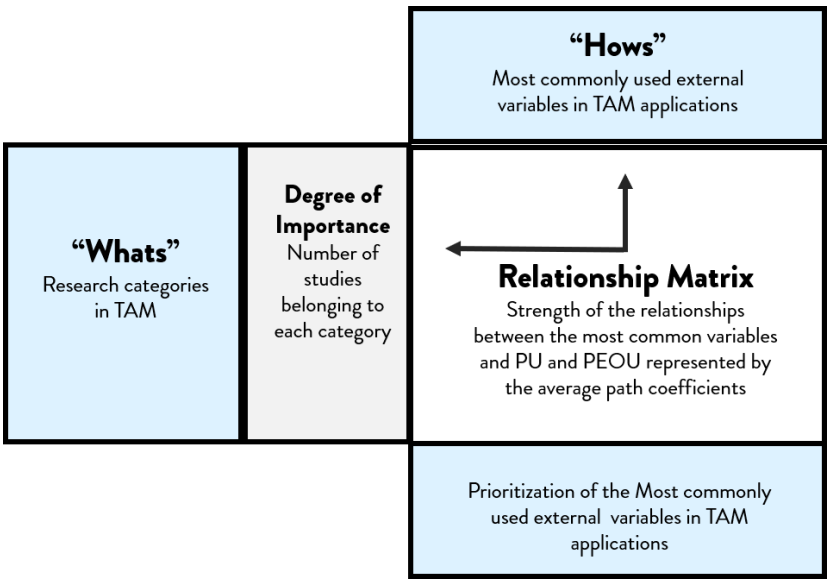


Figure 62: Proposed QFD matrix

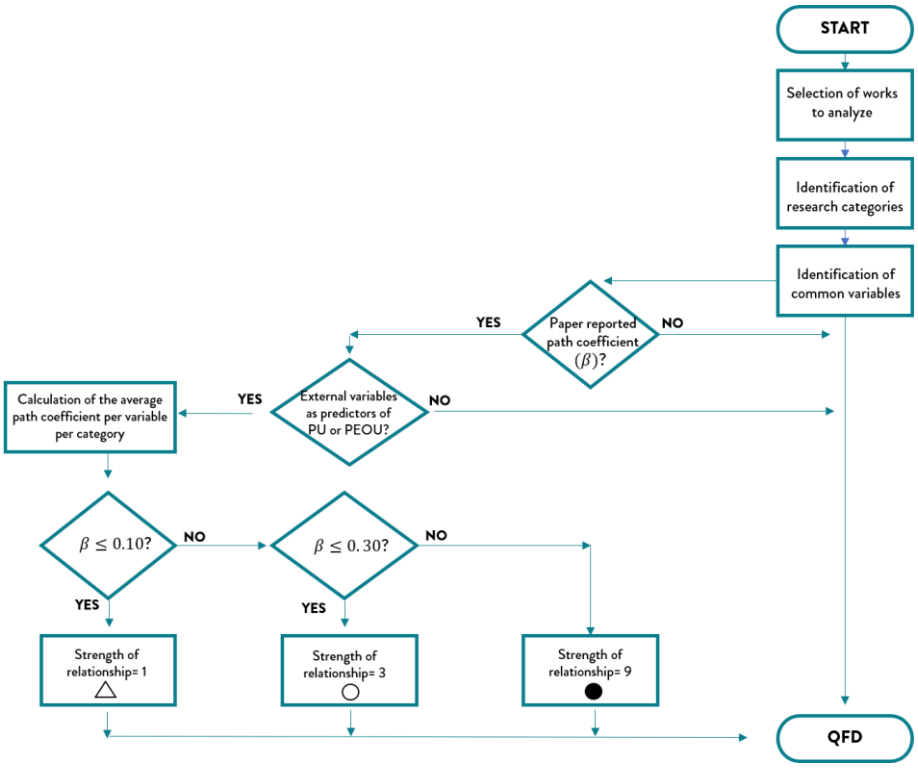


Figure 63: Papers selection process

7.4 Identification of Commonly Used External TAM Variables in e-Learning, Agriculture and VR Applications

To analyze the current state of the art of the TAM and apply QFD, we followed the selection criteria mentioned in the methodology and obtained a first sample of 67 papers. The selected works were further analyzed to identify types of applications and the recurrent variables used in TAM extensions.

7.4.1 Phase 1 - Definition of the "*What's*"

We started by analyzing the researchers' perspectives on the main objectives for the implementation of the TAM. In our study's QFD application, the customer requirements are represented by the different topics that our potential customers, i.e., the researchers, want to approach by using the TAM. We found that the topics could be divided into seven categories addressing the determinants of the acceptance of innovations, as shown in Table 34.

Table 34: Identified research categories

Defined Categories	Number of Studies
Technology acceptance: theoretical models	7
Acceptance of a bundle of technologies	6
Acceptance of a methodology	6
Acceptance of a device	8
Acceptance of a service/platform/system	30
Comparison of the acceptance among different tasks or technologies	3
Technology acceptance: the effect of certain moderating variables	7

7.4.1.1 Technology Acceptance: Theoretical Models

Works classified under this category include extensive literature reviews whose objective was to propose theoretical models to predict and evaluate the technology acceptance or systematically analyze previous empirical research. Abdullah and Ward [387] developed a General Extended TAM for e-learning (GETAMEL) by analyzing the external variables used in TAM extensions from the perspective of technology and user types. Similarly, Salloum et al. [413] explored the literature in the field of e-learning to identify the most commonly used external factors

explaining students' acceptance. The resulting model was validated with students of five universities in the United Arab of Emirates (UAE). Wingo et al. [432] organized a literature review considering each one of the constructs of the TAM2 and used the results to evaluate faculty's adoption of online teaching practices. In this same context, Scherer et al. [433] conducted a throughout literature review to deepen and synthesize TAM studies in digital technologies in education. The acceptance of everyday technologies in the context of education, such as mobile technologies, have been analyzed using TAM as in the work by Sanchez-Prieto et al. [434], who developed a model to evaluate teachers' intention to use mobile technologies in formal education. A more profound analysis of TAM applications in M-learning is presented in the research by Al-Emran et al. [417]. In the Virtual reality field, Tom Dieck and Jung [435] adopted a qualitative approach to identify the external dimensions influencing the acceptance of a mobile augmented reality application. The results were included in an extended TAM, especially useful for virtual reality innovations within the tourism sector.

7.4.1.2 Acceptance of a Bundle of Technologies

Empirical works grouped under this category measured the acceptance of a set of available technologies and practices analyzed as a whole and without making specific distinctions of any nature. For instance, Silva et al. [436] recognized the complementarity existing among sustainable agricultural practices and studied the adoption and use of Integrated Production technologies by Brazilian common beans' farmers. In an attempt to measure the potential acceptability of smart farm technologies for guava farmers in Thailand, Tubtiang and Pipatpanuvittaya [437] developed and validated an extension of TAM. Analyzing these technologies as a bunch was fundamental for determining the impact of their implementation in the farming supply chain. Far and Rezaei-Moghaddam [438] explored the experts, i.e., personnel and consultants' intention to use precision agricultural technologies (PA). Since PA is defined as a combination of ICTs allowing the technical and environmental optimization of resources in agriculture [439], we classified this study belonging to this category. Another bundle of techniques is that consisting of the available tools for food manufacturing. The paramount role of the food processing sector to overcome economic development challenges of the increasingly growing world population aroused the interest of Okumua et al. [440], whose study focuses on the acceptance of food processing technologies by micro and small entrepreneurs in Kenya. A recent work by Rezaei et al.[441] assessed the adoption of Integrated Pest Management (IPM) practices by Iranian tomato

growers. In the context of the study, PEST practices include cultural, mechanical, chemical, and biological strategies to reduce and refrain the negative impact of plant pests, improving farm sustainability [442]. As for the e-learning sector, Nam et al. [443] applied the TAM to investigate the ultimate effect of its constructs on the acceptance of assistive technologies by special education teachers. According to the definition provided by Cowan and Turner-Smith [444], assistive technology covers any device or system that makes possible the execution of a task safely and facilitates the performance, impossible to obtain otherwise.

7.4.1.3 Technology Acceptance When the Technology Is a Device

The TAM was initially conceived as a framework to understand the grounds for computer technology acceptance [388]. In keeping with its initial purpose, Teo et al. and Teo [445], [446] validated the TAM in an attempt to identify the factors predicting pre-service teachers' intention to use computers at the National Institute of Education in Singapore, and Wong et al. [447] studied teachers' intention to use computers in their pedagogical practices in a university in Malaysia. Analogously, Sanchez-Prieto et al. [448] examined the behavioral intention of primary education teacher students of the University of Salamanca, towards to use mobile devices for teaching practices to be developed in the future. Cellular technologies are attractive tools for educational purposes and also have a fundamental role in fostering rural development. With that in mind, Islam and Grönlund [449] surveyed the adoption reasons for mobile phones among farmers in Bangladesh. The proposed Rural Technology Acceptance Model (RUTAM) pointed out the significant influence of social ties at the early stages of adoption. Carrying on with the agricultural sector, Zhou and Abdullah [450] delved into the attributes responsible for a favorable reception of solar water pump (SWP) technology among rural farmers of Pakistan. The outcomes confirm the influence of PU and PEOU on SWP usage. On VR technologies, the TAM was tested to determine the acceptance of googles [451] and virtual reality devices in general [452]. In both cases, perceived enjoyment was a significant and positive predictor of attitude towards using and purchasing.

7.4.1.4 Technology Acceptance When the Technology is a Service/Platform/System

The number of articles belonging to this category is significantly higher than the others, totaling thirty-one works. The recurrent TAM applications of this nature can be due to the extensive Internet use and its paramount role in developing new technologies [453] thanks to the advantages it offers, such as speed and reliability

[454]. This categorization contains TAM applications to predict and evaluate the acceptance of specific software, systems, or platforms. The most customary TAM validation within the e-learning sector is to assess the acceptance of learning management systems (LMS) as in the works by Alharbi and Drew, Shin and Kang, Calisir et al., Mohammadi, Al-Rahmi et al., Binyamin et al., Al-Adwan et al., Fathema et al., Chang et al., Al-Gahtani and Lee et al. [455]–[465]. Regarding learning environments, contributions to TAM research have been made by Yeou, Estriegana et al. [466], [467] and Shyu and Huang [468], and authors like Wu and Chen and Revythi and Tselios [469], [470] have investigated the intention to benefit from online courses. Understanding users' motivations that trigger instructional resources acceptance is a key process in developing learning platforms and systems. Amongst the examined tools are Compliant Learning Object (SCLO) [471], educational wikis [472], web feeds [473], platforms supported by google sites and apps [474], as well as apps such as YouTube for learning assistance [475]. Moving to the agricultural field, Vidanapathirana et al. [476] tested an Online Agro-technology Diploma program from the TAM perspective. Moreover, innovative technologies like mobile-based agricultural services and information systems were under the scope of analysis of the work by Verma and Sinha, Verma and Sinha [477], [478] and Mercurio and Hernandez [401]. Some other interesting TAM implementations evaluated farmers' intention to use a microfinance platform [479], the acceptance of a QR Code for a food traceability system [389], and the usage of Cloud Computing technologies for farming in Ireland [480]. As for the VR sector, the contributions made by Huang and Liao and Huang et al. [481], [482] explored the determinants of acceptance of augmented-reality interactive systems.

7.4.1.5 Comparison of the Acceptance among a Set of Tasks/Technologies

TAM application in this type of study is not very diffused. Only three papers were found to analyze the TAM to understand users' preferences for specific techniques, technologies, or tasks over others. Broadly speaking, these studies evaluated how the TAM constructs, such as PU and PEOU, tilted the balance in favor of some innovations. In the agriculture field, Naspetti et al. [483] contrasted three environment-friendly production techniques: Agroforestry, Alternative protein source, and Prolonged maternal feeding, and validated the predictive power of PU over the intention to use. Caffaro et al. [402] tried to understand the factors responsible for the scarce adoption of smart farming technologies (SFTs). The authors clustered some SFTs into two groups: drones, sensors for data acquisition and automatic download, and agricultural apps belonging to the first type.

Agricultural robots and autonomous machines formed the second one. They also investigated the effect of exposure to different forms of interpersonal communication on PU and PEOU. As for the e-learning sector, schoonenboom [484] examined teachers' intention to use a learning management system for eighteen instructional tasks. The results showed that using the LMS is preferred for some activities, mainly due to task importance, LMS' usefulness for performing the job, and ease of use.

7.4.1.6 Acceptance of a Methodology

We found theoretical evidence that the TAM has been validated not only at the product/service level but also has the potential to predict the acceptance at process/practice level. Specifically, this category gathers papers analyzing the implementation of a particular methodology by looking beyond the mere technologies involved. Sharifzadeh et al. [485] examined the acceptance of a behavioral control strategy, namely, the use of Trichogramma spp for pest control by Iranian rice farmers, broadening the existent research body on crop protection techniques. Bahtera et al. [486] validated the TAM to provide a strategic perspective for the use of the internet in agricultural endeavors that is frequently overlooked. The authors emphasized the outstanding importance of marketing strategies for farmers' welfare and tried to understand the determinants of ICT use for this specific purpose. In the learning sector, e-learning and mobile learning, as well as mobile-based assessment, were analyzed from a methodology perspective. Several investigations look at students' acceptance of e-learning as a novel learning method. Punnoose [487] dug into the determinants of student's intention to study remotely by polling a sample of master scholars from the Assumption University of Thailand. This concern was also discussed in the research by Ibrahim et al. [488] validated with 95 undergraduate students at Tunku Abdul Rahman University College (TARUC). As for mobile learning, significantly fewer studies have addressed this methodology and analyzed its advantages and shortcomings over e-learning. Park et al. [489] investigated the process by which Konkuk university students adopted mobile learning and focused on the possibilities for learning evaluation through handheld or palmtop devices. Nikou and Economides [490] validated the TAM in the context of mobile-based assessment.

7.4.1.7 Technology Acceptance Analyzing the Effect of Certain Moderating Variables

In addition to the original TAM determinants, PU and PEOU, papers under this category give special attention to the moderating role of some variables being age and gender the most used. Ahmad et al. [491] applied an extension of the TAM in a public university in Malaysia to understand how age and gender affected the acceptance of computer-based technologies by faculty members. The results evidenced that the causal relationships among exogenous variables and the TAM were invariant for female and male staff members. However, age seemed to have moderating effects on the use of technology. In line with the previous study, Wong et al. [492] analyzed the influence of gender on student teachers' intention to use computers. Once more, the findings showed that gender had no moderating effects within the context of the study. Unlike the precedent researches, Padilla-Melendez et al. [493] found that females had a higher perception of playfulness and attitude towards the use of blended learning environments than males, and males, on the other hand, seemed to have higher intention to use this type of technology. Tarhini et al. [494] explored the moderating effect of age and gender in the students' acceptance of a Web-based learning system at Brunel University in England. The study outcomes reflected that younger students had a higher perception of usefulness, while older users perceived the system as more comfortable to use. Gender was also found to affect some of the relationships within the extended TAM. In addition to gender influence on TAM factors, Al-Azawei and Lundqvist [495] considered the effect of students' learning styles defined by Felder and Silverman [496], namely, active, sensing, visual and sequential learners, on user satisfaction towards an online learning system. No gender nor learning styles reported significant effects. Likewise, Al-Azawei et al. [497] assessed the impact of learning preferences in a blended e-learning system (BELS). They found no mediating relationships among those psychological traits and learner satisfaction or e-learning adoption. From a cultural approach, Tarhini et al. [498] investigated the effects of four cultural dimensions of individuals on the adoption of e-learning tools by students in Lebanon. The research included the factors of masculinity/femininity, individualism/collectivism, power distance, and uncertainty avoidance within the TAM. The validation process evidenced the existing relationship between culture and social norm, perceived usefulness, and perceived ease of use.

7.4.2 Phase 2 – Definition of the *"How's"*

The aim of this phase was to identify the external variables that academics and practitioners included more frequently in TAM extensions in order to approach the research purposes. After individuating the variables included in each one of the selected studies, we calculated the frequency of appearance of each one of the determinants. The most common variables are depicted in Table 35. The definitions of each one of the identified variables are provided in Table 36.

Table 35: Most commonly used external variables in TAM applications

External Variables	Included in the Proposed Model of Studies
Anxiety	7
Content quality	11
Experience	7
Facilitating conditions	10
Individual innovativeness	8
Perceived enjoyment	8
Self-efficacy	30
Service/System quality	7
Social norm	24

Table 36: Definitions of the "*How's*"

External Variables	Definition
Anxiety (ANX)	"An individual's apprehension, or even fear when she/he is faced with the possibility of using computers." [412], [499]. Negative and stressful feelings that users might experience when using the technology.
Content quality (CQ)	Extent to which the information fits user needs [500] in terms of information organization, relevance and actuality [501], availability of support materials, and accuracy of the terminology [460].
Experience (EXP)	Past interactions or exposure of an individual to a system and the accumulated knowledge gained by usage [502]–[504].
Facilitating conditions (FC)	Users' beliefs about the existence of technical and organizational resources and infrastructure to facilitate the use of technology [505].
Individual innovativeness (II)	Individual's disposition towards adopting any new technology before others [506], [507].
Perceived enjoyment (PE)	Refers to how pleasant and entertaining is the use of the innovation, separately from any performance consequence that can be deducted from system usage [434], [499], [508].

Self-efficacy (SE)	User's confidence in his/her capabilities to perform a task, achieve a specific goal, or produce the desired outcomes by properly using an innovative system or device [509]–[511].
System quality (SQ)	Technical achievements, the accuracy, and efficiency of the system [512].
Social norm (SN)	The extent to which the ideas coming from others may foster or discourage the use of technology [410], [411], [513].

7.4.3 Phase 3 - Strength of the Relationships and Relationship Matrix

It is a common interest among academics who develop TAM extensions, to comprehend the relationships existing between external variables and TAM's two main determinants PU and PEOU [387]. For this reason, two QFD matrices, one for each of the TAM's two primary constructs, were constructed, and considering that in the TAM, PEOU is also a determinant of PU [388], we included the construct PEOU within the PU matrix to analyze its effect. One of the most commonly reported statistical indexes in TAM studies is the Path coefficient (f). Path coefficients indicate not only the strength of the relationships but also the causal effect of the common external factors (independent variables) on the dependent variables (PU and PEOU) and the effect of PEOU on PU as depicted in Figure 64 [514].

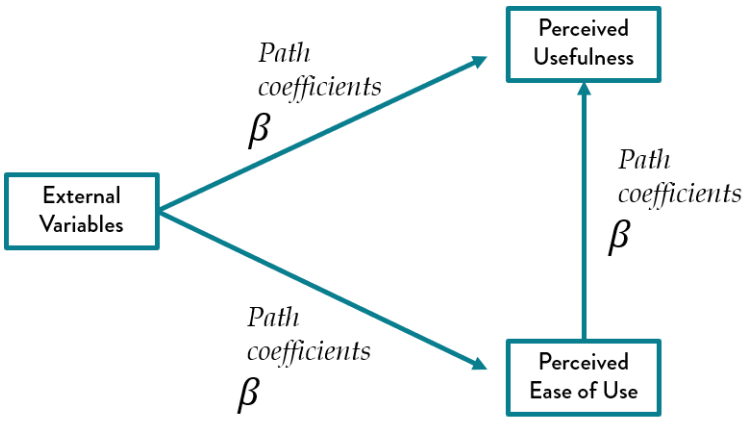


Figure 64: Path Coefficients

However, some of the analyzed studies did not report this information directly, and in some others, the independent and dependent variables were not directly linked. The number of works grouped in each category reporting the path coefficients is shown in Table 37. In addition, Table 37 specifies the quantity of studies reporting the relationship for each one of the TAM determinants, PU and PEOU.

Table 37: Number of papers reporting path coefficients *(fi)*.

Research Categories	Num. of Studies	Studies with *(fi)* w.r.t. PU	Studies with *(fi)* w.r.t. PEOU
Technology acceptance: theoretical models	7	3	3
Acceptance of a bundle of technologies	6	2	2
Acceptance of a methodology	6	3	3
Acceptance of a device	8	6	6
Acceptance of a service/platform/system	30	16	17
Comparison of the acceptance among different tasks/technologies	3	2	0
Technology acceptance: the effect of certain moderating variables	7	4	3

Deviating from the conventional QFD matrix in which the importance of customer requirements is assigned using a Likert scale of points 1 to 5, the degree of importance of our study's research problematics was determined based on the number of studies belonging to each category and reporting path coefficients. The relative importance was calculated as the coefficient of articles per category over the total of works reporting path coefficients.

For the relationship matrix construction, we assigned the values of the relationship between How's and What's using the average path coefficients between external variables and PU, external variables and PEOU, and between PEOU and PU. We followed the criteria suggested by Cohen [515]. Values in the range from 0 to 0.10 included were assigned the value of "1", reflecting a weak relationship. For indexes higher than 0.10 and up to 0.30 included, the importance was "3", indicating a medium relationship. Average coefficients higher than 0.30 were said to have a strong link and importance of "9".

Finally, the technical importance of external variables was calculated by the products' cumulative sum between the degree of importance of each category and the relationships' strength. The relative importance permitted the prioritization of the external variables. The discussion of the findings is presented in the following section.

7.5 TAM Extension proposal for FARMER 4.0

To understand the external variables that could influence the acceptance of a 3D learning environment for European farmers, we consulted previous TAM applications in e-learning, agriculture, and virtual reality sectors. TAM extensions on e-learning technologies have been a research topic for more than a decade [387]. On the contrary, significantly fewer studies investigated the acceptance of VR technologies, and that gap of knowledge is also mentioned in recent work by Sagnier et al. [516]. To facilitate the analysis, we considered the effects of the external variables in PU and PEOU separately. The impact of each factor per category is depicted in Figure 65 and Figure 66. As reported in Table 37, only two of the three researches belonging to the category: "Comparison of the acceptance among different tasks or technologies" provided information about path coefficients. However, none of them delved into the determinants of PEOU. On this basis, we excluded the mentioned category from the QFD matrix of PEOU. Considering that in the TAM, PEOU is also a determinant of PU [388], we included the construct PEOU within the PU matrix to analyze its effect.

Media of Path coefficient	Importance
0<B <= 0.10	1
>10 < B <=0.30	3
B>0.30	9

QFD based on the path coefficients of commonly used external variables w.r.t. Perceived Usefulness

Relationship Matrix			Degree of importance	Relative Importance	TAM	Commonly used External Variables								
●	Strong relationship	9 Points			PEOU	Anxiety	Content Quality	Experience	Facilitating conditions	Individual Innovativeness	Perceived Enjoyment	Self-efficacy	System Quality	Social Norm
○	Medium relationship	3 Points												
△	Weak relationship	1 Points												
Research categories														
Determinants of technology acceptance: theoretical models			3	0.083	○	△	△	○	○		●	○	△	○
Identify the determinants of acceptance of a bundle of technologies			2	0.056	○					○		○		△
Identify the determinants of acceptance of a methodology			3	0.083	●							○		○
Identify the determinants of technology acceptance when the technology is a device			6	0.167	●	△		△	△		●	○		○
Identify the determinants of technology acceptance when the technology is a service/platform/system			16	0.444	●	△	●	○	○	○	○	○	●	○
Identify the determinants of technology acceptance: comparison among a set of tasks/technologies			2	0.056										●
Identify the determinants of technology acceptance: moderating effects of certain variables			4	0.111	●							●		
TOTAL			36	1										

											TOTAL
Technical Importance	276	25	147	63	63	54	129	126	147	104	1134
Relative Importance	24%	2%	13%	6%	6%	5%	11%	11%	13%	9%	100%

Figure 65: QFD matrix for Perceived Usefulness

Media of Path coefficient	Importance
0<B <= 0.10	1
>10 < B <=0.30	3
B>0.30	9

QFD based on the path coefficients of commonly used external variables w.r.t. Perceived Ease of Use

Relationship Matrix			Degree of Importance	Relative Importance	Commonly used External Variables								
					Anxiety	Content Quality	Experience	Facilitating conditions	Individual Innovativeness	Perceived Enjoyment	Self-efficacy	System Quality	Social Norm
●	Strong relationship	9 Points											
○	Medium relationship	3 Points											
△	Weak relationship	1 Points											
Research categories													
Determinants of technology acceptance: theoretical models			3	0.088	○	△	○	●		○	●	△	○
Identify the determinants of acceptance of a bundle of technologies			2	0.059				●			●		
Identify the determinants of acceptance of a methodology			3	0.088							●		△
Identify the determinants of technology acceptance when the technology is a device			6	0.176	○		○	○		●	●		
Identify the determinants of technology acceptance when the technology is a service/platform/system			17	0.5	○	●	●	○	△	●	●	●	○
Identify the determinants of technology acceptance: moderating effects of certain variables			3	0.088							●		
		TOTAL	34	1									
													TOTAL
		Technical Importance			78	156	180	114	17	216	306	156	63	1286
		Relative Importance			6%	12%	14%	9%	1%	17%	24%	12%	5%	100%

Figure 66: QFD matrix for Perceived Ease of Use

In general, the findings suggest that the best predictor of PU is PEOU, followed by CQ and SQ, PE, SE, SN, FC, EXP, II, and finally, ANX. As for PEOU, it is mainly predicted by self-efficacy, followed by PE, EXP, SQ, CQ, ANX, SN, and finally, II. Therefore, we can confirm that the external variables have different effects on PU and PEOU.

PEOU is not considered as external variable because it is one of the TAM's two main determinants. Studies from the categories measuring the acceptance of a new methodology, a device, and a system or service, reported a strong predictive power of PEOU on PU. That was also the case for studies analyzing the moderating effect of some variables. A weaker but still significant influence of PEOU on PU was found in theoretical models and in cases-study evaluating the acceptance of a bundle of technologies. This study confirmed the presence of a strong and significant impact of the PEOU on PU in most cases, which validates the significance of the relationship established by Davis [388] in the original TAM.

The concept of ANX is often associated with negative feelings of nervousness, fear, and uncertainty about the outcomes of using innovations [448]. Li et al. [517] pointed out that in software applications, the effect of ANX is often analyzed, and that is evident in our study. Only works evaluating the acceptance of a device and a system or service, and theoretical extensions of the model, reported the causal link among ANX and the two main TAM determinants. The average effect size evidenced a weak relationship between ANX with PU and a medium impact on PEOU. These results are in line with the investigation conducted by Van Raaij and

Schepers [518], who reported a direct effect of ANX on PEOU and an indirect effect on PU.

CQ is a variable especially crucial in learning platforms. By designing and organizing the content in a challenging, reasonable, appropriate, and understandable manner, users' autonomy and competence may be enhanced [490]. Solely researchers interested in assessing the acceptance of systems/platforms/or services, which belong to the same category, and theoretical works, registered the direct effect of CQ on PU and PEOU. Theoretical studies reported a weak influence of CQ in PU and PEOU. On the contrary, PU and PEOU of systems, platforms, and services are strongly affected by the CQ. The influence of CQ on PU and PEOU mentioned in the last category is in accordance with the study conducted by Almaiah et al. [519], who reported that CQ has positive effects on the two TAM beliefs.

According to Venkatesh and Bala [412], increasing the EXP will give the user a better idea about the required effort to develop a specific task using the technology [520], [521] and may also create a favorable feeling about system usefulness [465], [522]. In line with those authors, our findings suggest that previous interactions with innovations have a larger effect on PEOU than in PU. Specifically, EXP has a strong predictive influence in PEOU and a medium impact on PU in the systems' acceptance category. In the case of devices' acceptance, prior use has a moderate effect on PEOU and little effect on PU. Literature reviews examined in our study found that EXP has moderate importance in determining PU and PEOU.

FCs are a measure of the available resources to support a given behavior [448], [450], and the expertise required [415]. Similarly to Cheng et al. [523], we also found evidence that FC can enhance the idea of how easy it can be to perform a task. Our study's outcomes indicate that users' perception of FC is a crucial determinant of PEOU when the acceptance of a set of complementary technologies is being assessed. FC's decisive role in determining the PEOU was also evident in theoretical studies, which in turn reported a medium impact of FC in PU. We also found that when the technology was a system or service, FCs have a medium influence in PU and PEOU. When the research interest was to predict a device's acceptance, FC moderately affected PEOU and slightly determined PU of this type of technology. One of the most noteworthy findings suggests that users' PEOU of a bundle of innovations will be strongly influenced by the FC associated with the

complementarity of those technologies. Additionally, FC's role is more appreciated when it comes to the use of platforms than in the case of a device.

II is considered a personal trait. An innovative person will be eager to face the risks associated with the early stages of technology readiness and will have more definite intentions to use new IT [524]. We observed that this external factor has a medium-sized relationship with PU in situations in which users have to express their preferences from a group of technologies available. II also moderately influences PU of systems, services, or platforms. For this same category, the importance of II seems to be considerably less in PEOU. Only studies concerning the acceptance of systems reported the relationship between II and PEOU, indicating that its effect is insignificant on PEOU for our research categories.

PE is understood as an intrinsic motivational factor [525]. PE is a significant predictor of PEOU in the context of devices and systems or services acceptance scenarios. The theoretical category reported a medium strength of the relationship between PE and PEOU. PU is also primarily affected by PE of using devices, and this is in line with the category of theoretical studies. As for systems and services, PE has a medium impact on PU.

Compeau and Higgins [510] stated that the higher the SE expectations, the higher likelihood of succeeding in a particular assignment. The effect of SE as an external variable is the most studied in the TAM works we analyzed. Only one category out of seven didn't report the relationship between SE and PU or PEOU, namely, studies comparing a set of technologies. In all the other research topics, SE showed a significantly strong influence on the perception of how easy could be to use technology, as Venkatesh and Davis [526] suggested. For PU, the predictive power of SE was strong when moderating variables such as gender and age were being contemplated. All the other categories mentioned a medium effect of SE in PU.

As can be expected, the SQ is particularly relevant for studies analyzing the acceptance of a system or service. If a platform does not run smoothly, users may lose interest in using it, and their perception of ease of use will decrease, as well as their satisfaction [527], [528]. Our study confirmed the results obtained by Almaiah et al. [519], pointing out that SQ has a substantial impact on PU and PEOU of platforms and systems. In contrast, the theoretical studies category reported a minimum effect of SQ on both TAM's determinants.

The logic behind SN is that human behavior is somehow affected by the opinions of the individuals' closer social spheres. In some cases, people may use a technology based on others' perceptions about the convenience of the use over their own emotions and beliefs [409]. Our results suggest that social pressure can have a more significant influence on users' perceptions of usefulness than in PEOU. Academic works comparing the acceptance of a set of technologies reported that users tend to perceive innovations as more useful, based on the recommendations of individuals closest to them. In those cases, SN seems to have a strong predictive power on PU. Theoretical studies and research investigating the acceptance of methodologies, devices, or systems, showed a medium explanatory impact of SN in PU. When innovations are considered a bunch of technologies, SN had a low effect on PU. Concerning PEOU, theoretical studies registered a moderate effect of SN on this TAM determinant, as well as studies assessing the acceptance of systems. When the acceptance of a methodology is under analysis, SN seems to have little effect on PEOU.

The main findings and correlations are summarized in Figure 67. Only variables reporting a more significant influence in the two TAM's beliefs are included for each of the seven study categories. Common factors used in TAM extensions in the fields of interest are also listed.

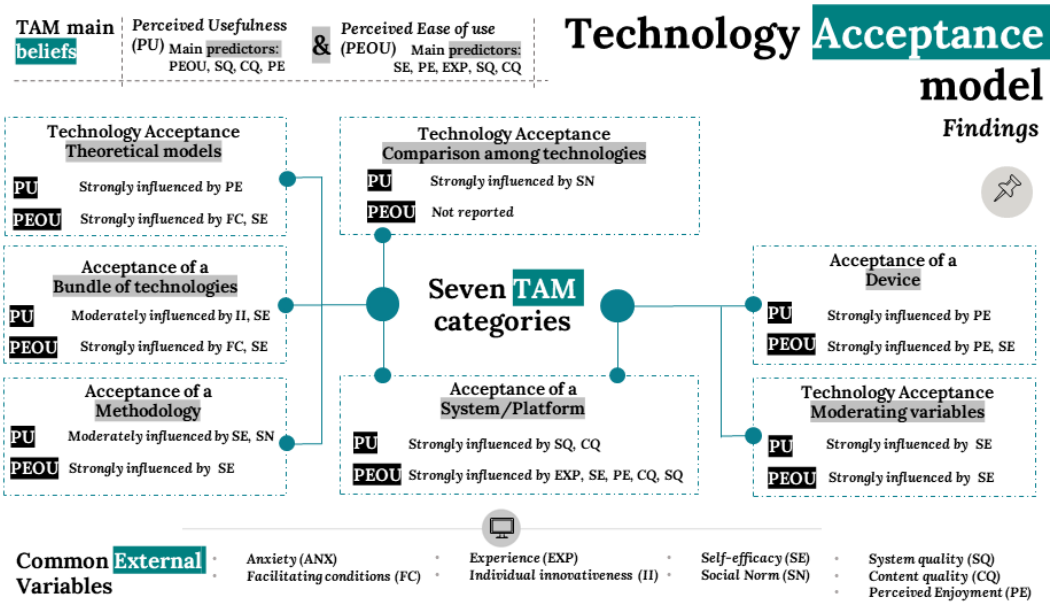


Figure 67: Summary of findings

Based on the previous analysis, the TAM extension that better fits the context of the e-learning tool FARMER 4.0. is depicted in Figure 68. The validation of the proposed model corresponds to the subsequent phase of the present study and will be developed in the near future.

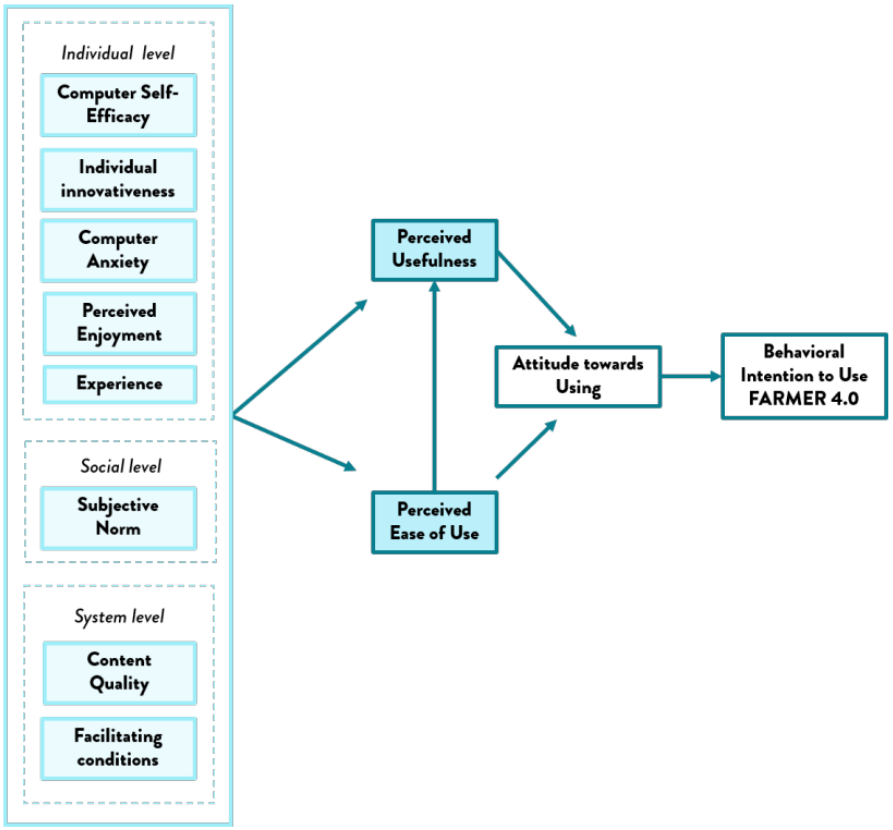


Figure 68: Proposed TAM extension for FARMER 4.0

7.6 Validation of the proposed TAM Extension

Dodero et al. [529] pointed out the complexity of e-learning systems due to the diversified nature of projects, the stakeholders, and system features and highlighted the importance of specific methodological approaches for an accurate design, development, and assessment. This perspective is very pertinent considering the intricate context of the e-learning platform FARMER 4.0 and the associated learning by doing training model in a relatively low technological sector like farming. For this reason, in the previous sections, we conducted a literature review on TAM applications in the three sectors that converge in the e-learning tool

(agriculture, e-learning, and virtual reality), aiming at identifying the external variables to include in a TAM extension to assess the adoption of FARMER 4.0. Using the QFD as an organizing framework, we identified the research problematics and the most commonly used external variables included to assess technology acceptance. One of the research categories and the one that fits the context of FARMER 4.0 is "Technology acceptance when the technology is a platform or system". Findings suggest that the most common external variables included in this type of TAM extension were ANX, CQ, EXP, FC, II, PE, SE, and SN. Table 36 presents the definitions of these variables. The TAM extension proposed, which will be validated in the following sections, is shown in Figure 68.

7.6.1 Validation Hypothesis

In line with the previous findings, we stated the hypothesis listed in Table 38. We expected farmers' PEOU and the CQ to have a strong positive influence on the PU of the e-learning tool FARMER 4.0 (H10; H1a). The constructs EXP, FC, II, PE, SE, and SN were expected to have a medium positive impact on PU (H2a; H3a; H4a; H5a; H6a; H7a). A low negative influence of ANX on PU was also predicted (H8a). Furthermore, the external variables with a strong positive impact on PEOU were expected to be CQ, EXP, PE, and SE (H1b; H2b; H5b; H6b). PEOU was also expected to be moderately influenced by FC, SN, and ANX (H3b; H7b; H8b) and only slightly influenced by II (H4b). Additional hypotheses were included to test the predictive power of PU and PEOU on the ATT (H9a; H9b) and to measure the influence of ATT on the ultimate BI of farmers to use the FARMER 4.0 e-learning tool (H11). The strength of the relationships will be validated on the basis of path coefficients according to the criteria established by Cohen [515]. Path coefficients reporting values below or equal to 0.10 denote a low influence. External variables reporting path coefficients ranging from 0.1 to 0.30 included will be considered as having a moderate predictive power. Finally, higher path coefficients entail a strong causal relationship.

Table 38: Research hypothesis

Hypothesis	Definition
H1	***(H1a).*** Content quality will have a positive influence on PU ***(H1b).*** Content quality will have a positive influence on PEOU
H2	***(H2a).*** Experience will have a positive influence on PU ***(H2b).*** Experience will have a positive influence on PEOU

H3	***(H3a).*** Facilitating conditions will have a positive influence on PU ***(H3b).*** Facilitating conditions will have a positive influence on PEOU
H4	***(H4a).*** Individual innovativeness will have a positive influence on PU ***(H4b).*** Individual innovativeness will have a positive influence on PEOU
H5	***(H5a).*** Perceived enjoyment will have a positive influence on PU ***(H5b).*** Perceived enjoyment will have a positive influence on PEOU
H6	***(H6a).*** Self-efficacy will have a positive influence on PU ***(H6b).*** Self-efficacy will have a positive influence on PEOU
H7	***(H7a).*** Social norm will have a positive influence on PU ***(H7b).*** Social norm will have a positive influence on PEOU
H8	***(H8a).*** Anxiety will have a negative influence on PU ***(H8b).*** Anxiety will have a negative influence on PEOU
H9	***(H9a).*** Perceived Usefulness (PU) will have a positive influence on attitude towards using (ATT) ***(H9b).*** Perceived Ease of Use (PEOU) will have a positive influence on attitude towards using (ATT)
H10	Perceived Ease of Use (PEOU) will have a positive influence on PU
H11	Attitude towards using (ATT) will have a positive influence on the Behavioral Intention to Use the e-learning tool FARMER 4.0

7.6.2 Description of the Questionnaire

The development of the questionnaire used in the present study followed an initial screening of the items included in similar TAM validations. After further analysis of their relevance and pertinence, 36 items were retained and adapted in wording to fit the context of FARMER 4.0.

The questionnaire was structured in four sections. In the first section, a general description of the purpose of the study, together with a mini-guide on the system usage, was given. Respondents were also provided with the link to access FARMER 4.0 website and were asked to explore it. Within the second section, we asked participants for their consent for personal data processing in line with data protection regulations. The third section included demographic questions about age, gender, education level, computer use frequency, and previous experience in e-learning systems and farming activities. Finally, the fourth section included 36 items aiming to assess BI (3 items), ATT (3 items), PU (3 items), PEOU (3 items), ANX (3 items), CQ (3 items), EXP (3 items), FC (3 items), II (3 items), PE (3 items), SE (3 items), and SN (3 items). Each item was measured using a seven-point Likert Scale, being 1 = strongly disagree; 2 = moderately disagree; 3 = somewhat disagree; 4 = neutral; 5 = somewhat agree; 6 = moderately agree, and 7 = strongly agree. Items are listed in Appendix A.

The items selected for the present research were applied in previous TAM studies showing adequate validity and reliability for the contexts of application. Items initially in English were translated into Italian. The adequacy of the translation was verified by Italian researchers. The analyzed variables and the source from which items were adopted are listed in Table 39.

Table 39: Questionnaire items source

Variable	Items Source
BI	Davis [409], Taylor and Todd [530], Gangwar et al. [531]
ATT	Davis [409], Fathema et al. [462], Chuah et al. [390].
PU	Davis [409], Chuah et al. [390], Davis et al. [414].
PEOU	Davis [409], Manis and Choi [451], Venkatesh et al. [505], Teo [532].
ANX	Venkatesh et al. [505], Venkatesh and Bala [412], Faqih and Jaradat [533], Sanchez-Prieto et al. [448].
CQ	Lee and Lehto [475], Cheong and Park [534], Salloum et al. [413].
EXP	Taylor and Todd [530], Alharbi and Drew [455].
FC	Davis [409], Fathema et al. [462], Cheung and Vogel [474].
II	Agarwal and Prasad [506], Natarajan et al. [535].
PE	Manis and Choi [451], Salloum et al. [413].
SE	Sanchez-Prieto et al. [448], Lee and Lehto [475], Venkatesh [536], Lee et al. [465], Compeau and Higgins [510].
SN	Koenig-Lewis et al. [393], Wu and Chen [469].

7.6.3 Data Collection

Our target was people with experience in farming-related activities. Similarly to Pappas et al. [537], we gathered an initial sample of 42 people by using convenience snowball sampling. Considering the restrictions associated with personal encounters in times of COVID-19, and in line with a vast majority of TAM validations [538], we used an online survey for data collection.

The designed questionnaire was sent using the Google survey tool. Responses were collected from mid-January to the end of April 2021. All 42 questionnaires were complete and valid.

7.7 Results

Demographic information was summarized using the IBM Statistical Package for Social Science (SPSS) software, similarly to Makransky and Lilleholt [539]. Results are depicted in Table 40. A slight majority of respondents were females (23 out of 42). A high educational level and high frequency of computer use were reported by participants. Twenty-one percent of respondents have experience in agricultural activities of more than 20 years, whereas the 45% have less than 5 years of experience in farming-related activities.

To further examine the causal relationships between the proposed model's variables and the corresponding path coefficients, the Structural Equation Modeling (SEM) approach was considered the most appropriate. The SEM is a set of techniques that, by combining factor analysis and multiple regression analysis, allow the study of relationships between one or more independent variables and one or more dependent variables [540].

The discussion by Bagozzi [541], reported by Chau [542], and more recently by Al-Gahtani [464], exploring the several advantages of the SEM in similar studies, supports the use of SEM techniques for the present research. Some of the reasons that favor the implementation of SEM over other multiple regression analyses (MRA) include the possibility of making explicit a research theory by defining it in specific constructs, formulate hypotheses about existing relationships between the different constructs, and test the theory and the designed measurements. The software used to adopt the SEM approach in the present work was the Smart PLS version 3. This software is based on least-squares estimation to adopt the SEM (PLS-SEM). The PLS-SEM was preferred as the analysis method for this study considering the minimal demands on measurement scales, the sample size, the number of constructs [464], [543], and its increasing popularity in analyzing path-coefficients in research models [494].

Table 40: Basic information of the sample

Characteristic		Frequency	Percentage
Gender	Female	23	55%
	Male	19	45%
	20-35 years	19	45%
Age	36-50 years	8	19%
	More than 50 years	15	36%
Education Level	Literate w/o qualification	3	7%

	School	5	12%
	Graduate	16	38%
	Post-Graduate	18	43%
	High	24	57%
Frequency of computer use	Moderate	9	21%
	Low	6	14%
	Sparse	3	7%
Experience in similar systems	No	13	31%
	Yes	29	69%
	More than 20 years	9	21%
Experience in agro-activities	11-20 years	6	14%
	5-10 years	8	19%
	Less than 5 years	19	45%
Total of participants		42	100.0%

For a suitable PLS assessment, Aparicio et al. [544] suggested that the sample size should satisfy at least one of the following conditions: (i) be ten times the largest number of items or questions used to measure one construct, or (ii) be ten times the largest number of paths associated with a particular construct. In our case study, the highest number of questions to measure one construct was three, entailing a minimum sample size of 30 to satisfy one of these conditions. Therefore, our sample, consisting of 42 respondents, is acceptable. Furthermore, a weaker rule also suggested by Chin et al. [543] is to multiply the number of questions or the number of paths by five instead of ten. Using this rule, we manage to satisfy both conditions as the larger number of paths in our case study is eight, resulting in a minimum suggested number of 40.

The proposed model's testing followed a two-step approach as in the work by Rezaei et al. [441], following the suggestion made by Bamberg [545]. According to this approach, the first step corresponds to the verification of the quality of the instrument (questionnaire) used to validate the model (measurement model). The second step evaluates the hypothetical relationships among the constructs (structural model).

7.7.1 Measurement Model Validation

The quality of the items was assessed in terms of their reliability and validity. Reliability refers to the extent to which a test is likely to yield the same results in case of repetition. On the other hand, the validity reflects the level at which an item effectively measures what it wants to measure [546].

Construct validity and reliability were evaluated in terms of internal consistency through Cronbach's Alpha (CA), the Average Variance Extracted (AVE), and the composite reliability (CR). Similarly to the study by Rajan and Baral [547], we verified the following criteria suggested by Hair et al. [548] to ensure the validity and reliability of the measured constructs in the present study.

- Item loadings should exceed 0.7 [549], [550].
- Composite reliability (CR) must be greater than 0.7 [548], [551].
- The average variance extracted (AVE) for each factor should be larger than 0.5 [552].
- Cronbach's coefficient alpha (CA) should be above 0.7 [553].

The discriminant validity (DV) is also frequently reported in similar TAM validations as in the work by Cidral et al. [554]. The discriminant validity examines the extent to which the scale measuring a specific construct is different from the ones of other constructs [552]. Based on the criterion established by Fornell and Larcker [552], a model has acceptable discriminant validity if the variance that a variable has with its constructs is higher than the variance shared by the variable with the others.

After running the PLS algorithm, some of the items showed loadings below 0.7, the minimum suggested to ensure reliability, and therefore were no longer considered. A second calculation was run after dropping the items EXP2, EXP3, and PEOU3. The results of the second run are depicted in Table 41.

Table 41: Constructs reliability and validity

Variable	Items	Mean	Variance	STDEV	CA	AVE	CR
ANX	3	2.714	2.785	1.661	0.919	0.860	0.949
ATT	3	5.929	1.015	1.002	0.858	0.780	0.914
BI	3	5.778	1.333	1.141	0.832	0.748	0.899
CQ	3	5.659	1.259	1.121	0.831	0.747	0.899
EXP	1	5.143	2.511	1.584	1.000	1.000	1.000
FC	3	5.595	1.061	1.027	0.777	0.692	0.870
II	3	5.238	2.685	1.635	0.905	0.840	0.940
PE	3	5.595	1.234	1.106	0.863	0.783	0.915
PEOU	2	4.944	2.491	1.570	0.945	0.948	0.973
PU	3	5.754	1.283	1.130	0.858	0.779	0.913
SE	3	5.190	2.273	1.507	0.918	0.859	0.948
SN	3	5.397	1.713	1.307	0.844	0.764	0.907

Mean scores for almost all the variables were higher than the midpoint value of the scale, 3.5, except for anxiety. This indicates that most of the respondents did

not experience stress of negative feelings when interacting with the e-learning tool. Standard deviation values ranged from 1.002 to 1.661, showing that values are moderately spread around the mean.

All the constructs showed satisfactory levels of validity and reliability. Loadings of all items were higher than 0.7. Composite reliability for all constructs was above the 0.7 threshold, with values from 0.870 to 1.000. AVE scores ranged from 0.692 to 1.000, exceeding the 0.5 as suggested by the literature. Cronbach's Alphas were higher than 0.7, ranging from 0.777 to 1.000. Discriminant validity of the model was also satisfactory as shown in Table 42. The square root of the AVE of each variable (value in the diagonal) is higher than the other correlation values. Therefore, the measurement model was validated.

Table 42: Correlation between constructs and the square root of AVEs

	ANX	**ATT**	**BI**	**CQ**	**EXP**	**FC**	**II**	**PE**	**PEOU**	**PU**	**SE**	**SN**
ANX	0.928											
ATT	-0.307	0.883										
BI	-0.392	0.824	0.865									
CQ	- 0.170	0.734	0.721	0.864								
EXP	-0.406	0.422	0.485	0.172	1.000							
FC	-0.410	0.704	0.695	0.713	0.292	0.832						
II	-0.571	0.359	0.466	0.266	0.689	0.306	0.916					
PE	-0.415	0.727	0.772	0.809	0.426	0.637	0.563	0.885				
PEOU	- 0.485	0.464	0.588	0.428	0.776	0.396	0.713	0.646	0.974			
PU	-0.251	0.734	0.723	0.723	0.364	0.621	0.549	0.834	0.505	0.882		
SE	-0.544	0.503	0.573	0.519	0.672	0.473	0.837	0.736	0.784	0.687	0.927	
SN	-0.399	0.735	0.854	0.785	0.462	0.673	0.434	0.828	0.632	0.748	0.616	0.874

7.7.2 Structural Model Validation

For the examination of the model fit, the function of Bootstrapping of the Smart PLS Software was used. This function allows verifying the significance of the relationships among the different variables. In this case study, the test used 5000 sub-samples with 0.05 of significance level in one-tailed test, similarly to Estriegana et al. [467]. We started by analyzing the TAM as proposed by Davis et al. [414], and then we moved to the extended TAM version designed for the context of FARMER 4.0.

To determine the predictive power of the model, the coefficient of determination was considered. The coefficient of determination (R^2) measures the percentage of the variance of the dependent variable that can be attributed to the independent variable. Falk and Miller [555] suggested that for a model to have a minimum explanatory power, R^2 should be significant ($t > 1.64$) and greater than 0.10. Values of R^2 range from 0 to 1, and the higher the value, the better. Table 43 shows the R^2 values considering only the original TAM. All values were above 0.10, reflecting an acceptable predictive power.

Table 43: TAM in the context of FARMER 4.0: Structural Model.

Variable	R^2	Mean	STDEV	T Stat.	p Value	Significant
ATT	0.560	0.593	0.091	6.145	0.000	Yes
BI	0.709	0.727	0.057	12.357	0.000	Yes
PU	0.258	0.273	0.101	2.553	0.005	Yes

The TAM, as proposed by Davis [388] (see Figure 69), is able to explain 70.9% of the variance of farmers' behavioral intention (BI) to use the e-learning tool. Furthermore, 56% of farmers' attitude toward use (ATT) is explained jointly by PU and PEOU. PEOU is apparently responsible for 25.8% of the variance of PU.

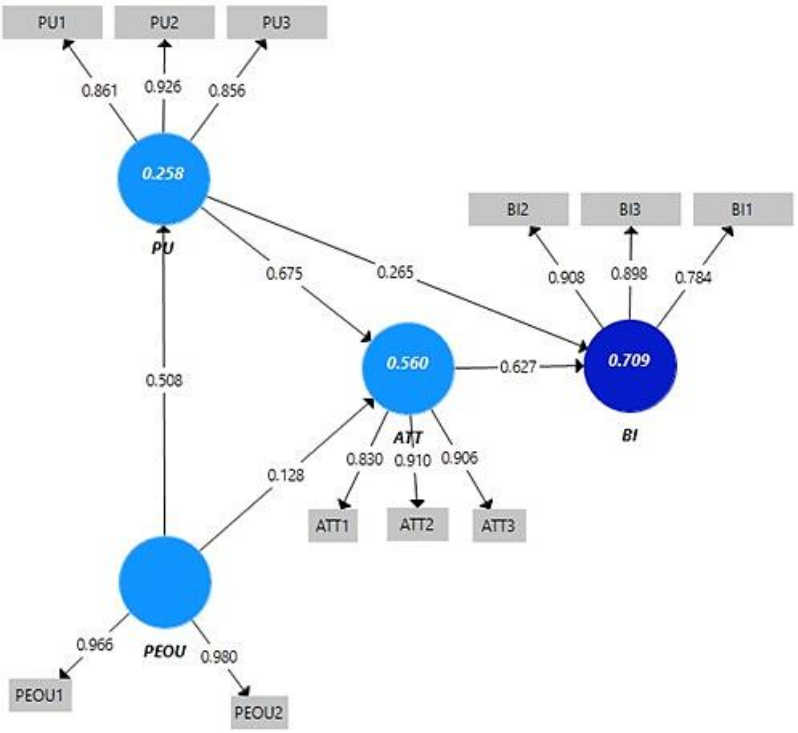


Figure 69: TAM validation

Path coefficients are numerically represented on the arrows connecting the different variables in Figure 69. The strength of path coefficients (SPC) and their significance are shown in Table 44. Farmers' attitude towards the e-learning tool influences their intention to use it (β = 0.627), jointly with their perceptions about the usefulness of the tool (β = 0.265). In turn, the attitude towards using the e-learning tool (ATT) is strongly affected by PU (β = 0.675), but the effect of PEOU on the ATT is weak and statistically not significant (β = 0.128. No sig.). Finally, PEOU has a positive and significant effect on PU (β = 0.508). This initial analysis suggests that farmers give the utmost importance to the perceived usefulness of innovations or technologies when considering using them. For the specific context of the study, the TAM version proposed by Davis et al. [414] does not hold entirely. However, it is still a valid aid to describe the adoption behavior of the e-learning tool FARMER 4.0.

Table 44: Original TAM: path significance using percentile bootstrap 95% confidence interval

Path	SPC	Mean	STDEV	T Stat.	p Value	Significant
ATT ^ BI	0.627	0.642	0.109	5.771	0.000	Yes
PEOU ^ ATT	0.128	0.124	0.176	0.726	0.234	No
PEOU ^ PU	0.508	0.512	0.101	5.023	0.000	Yes
PU ^ ATT	0.675	0.680	0.090	7.490	0.000	Yes
PU ^ BI	0.265	0.254	0.139	1.908	0.028	Yes

After validating the TAM as proposed by Davis et al. in 1989, we assessed the proposed TAM extension following the same process. However, the model as proposed in Figure 68 showed a neutral fit considering the observed data (χ^2=977.492; NFI = 0.534; the closer the Normed fit index (NFI) to 1, the better the fit [556]). For this reason, similarly to Naspetti et al. [483], we implemented the post hoc model-fitting strategy suggested by Byrne [557] to modify the model and obtain a better fit. Following this model-fitting strategy, every external variable and the corresponding paths were incorporated to the TAM variables and then tested. After several iterations and based on other statistical and theoretical considerations, only the most significant constructs and paths were retained. The final model, presented in Figure 70, showed a significantly better fit (χ^2= 262.742; NFI = 0.682). The associated determination coefficients (R^2), as well as path coefficients, are presented in Table 45 and Table 46.

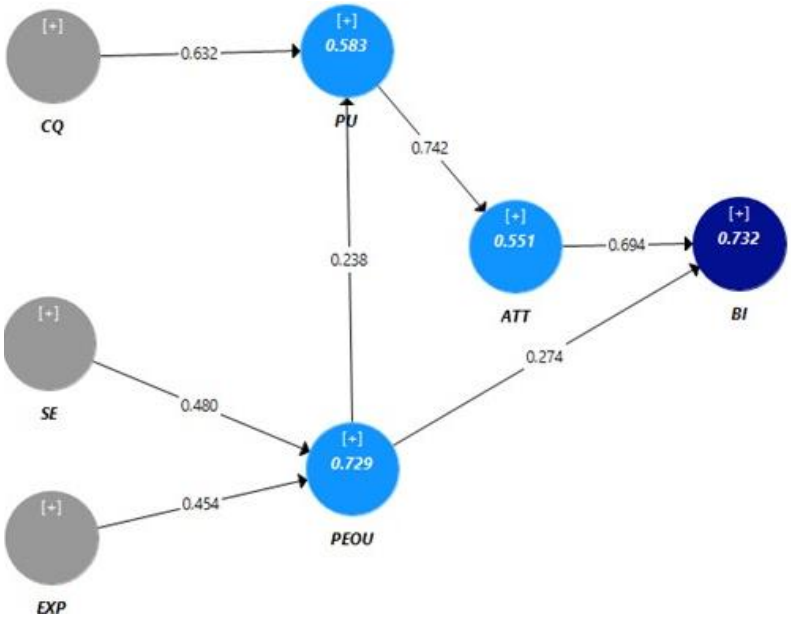


Figure 70: Modified TAM extension for Farmer 4.0

In this new TAM extension, taking into account the results of the initial TAM validation, the relationship between PEOU and ATT was removed as it was found to be not significant. However, PEOU was found to have a moderate influence on farmers BI to use the e-learning tool (β = 0.274). PEOU is influenced strongly by SE (β = 0.480) and EXP (β = 0.454), which jointly explain approximately 72.9% of its variance. The main determinant of PU was found to be CQ (β = 0.632), and both CQ and PEOU (β = 0.238), are responsible for 58.3% of PU variance. PU is strongly associated with farmers' attitude towards use (β = 0.742) and explains 55.1% of ATT variance. In general, the model is able to explain 73.2% of farmers' intention to use the platform. The strongest determinant of BI is ATT (β = 0.694).

Table 45: New Extended TAM: Structural Model

Variable	R^2	Mean	STDEV	T Stat.	*p* Value	Significant
ATT	0.551	0.562	0.070	7.866	0.000	Yes
BI	0.732	0.745	0.045	16.201	0.000	Yes
PEOU	0.729	0.743	0.063	11.605	0.000	Yes
PU	0.583	0.612	0.126	4.640	0.000	Yes

Table 46: New TAM Extension: path significance using percentile bootstrap 95% confidence interval

H	Results	Path	SPC	Mean	STDEV	T Stat.	*p* Value	Significant
H11	Accepted	ATT ^ BI	0.694	0.697	0.070	9.858	0.000	Yes
H1a	Accepted	CQ ^ PU	0.632	0.644	0.117	5.390	0.000	Yes
H2b	Accepted	EXP ^ PEOU	0.454	0.452	0.128	3.539	0.000	Yes
N/A	N/A	PEOU ^ BI	0.274	0.279	0.069	3.953	0.000	Yes
H10	Accepted	PEOU ^ PU	0.238	0.237	0.104	2.302	0.011	Yes
H9a	Accepted	PU ^ ATT	0.742	0.748	0.047	15.760	0.000	Yes
H6b	Accepted	SE ^ PEOU	0.480	0.487	0.124	3.882	0.000	Yes

Based on this new TAM extension and considering the criteria established by Cohen [515], SE and EXP have a **strong** positive causal relationship with PEOU (H6b and H2b). CQ has a **strong** positive impact on PU (H1a). PU showed a **strong** effect on ATT (H9a), which in turn has a **strong** effect on BI (H11). The casual relationship between PEOU and BI was not included in any of the hypotheses, but it was found to exist and be **moderate**.

This adjusted and validated TAM extension allows the identification of critical drivers of acceptance for FARMER 4.0. Furthermore, the revised model offers a more reliable perspective when designing e-learning systems in future agricultural applications to foster users' acceptance.

7.8 Discussion

Survey results evidenced that farmers and agricultural entrepreneurs have a positive attitude towards the e-learning tool (ATT) and manifested the intention to use it (BI). Among the two main TAM determinants, respondents perceived the tool to be more useful (PU) than easy to use (PEOU).

The system's most highly feature rated was the quality of the content (CQ) offered through the several courses. A positive perception of the available help and guidelines offered by FARMER 4.0 to facilitate navigation (FC) was also noted. Concerning personal traits, participants manifested a moderate level of enjoy using the platform (PE). Most of the respondents displayed acceptable levels of experience using similar e-learning platforms (EXP). This was reflected in low levels of anxiety (ANX) and acceptable self-efficacy (SE) reported by individuals

when exploring the tool. As for the social level, interviewees declared that their closest social sphere would also approve the tool's use (SN).

The TAM proved to be a very helpful theoretical approach to explain farmers' intention to use the FARMER 4.0 e-learning environment. Accordingly, farmers' perception of the usefulness of the tool (PU) was found to have a strong and significant impact on their attitude towards use (ATT), which stands out as the primary determinant of farmers' intention to use (BI).

The TAM extension proposal built based on the literature showed an improvable model fit for the current context of analysis. For this reason, we identified a new TAM extension that better suits the FARMER 4.0 context. The final model showed that potential users of FARMER 4.0 would perceive the e-learning tool to be useful (PU), depending on their perceptions about the quality of the content (CQ) in terms of its relevance and its alignment with their specific information needs. To a lesser extent, PU was also influenced by the PEOU. In turn, PEOU was found to be determined by EXP and SE, two variables highly correlated among them. Similar results were reported by Chang et al. [463] and Calisir et al. [457].

Model validation results also suggest that PEOU is a predictor of BI rather than a determinant of ATT. The absence of a significant causal effect of PEOU on ATT is in line with the results obtained by Tarhini et al. [473] or by Davis [409], who later re-considered the model by eliminating ATT [526]. However, unlike previous studies, ATT seems to mediate PU and BI's relationship, like in the work by Vidanapathirana et al.[476].

To sum up, farmers' intention (BI) to use the e-learning platform FARMER 4.0 will mainly depend on their ability to interact with the several features (PEOU) and the attitude (ATT) they have formed about how advantageous the platform is. Important external variables that shape farmers' perceptions about the PU and PEOU of the e-learning tool are self-efficacy (SE), previous experience with similar systems (EXP), and the quality and pertinence of the information available (CQ). Although relatively different from the initially proposed TAM extension, the model offers better adequacy, keeping a reduced number of constructs. Improvement efforts addressing the pinpointed variables will be more appreciated by users of FARMER 4.0 and similar e-learning systems.

7.9 Conclusions

The present study was developed in the context of an agricultural project in Europe. Our first objective was to conduct a literature review to identify the most common external variables used in TAM applications using the QFD to give structure to the research. Our analysis focused on three sectors, namely, e-learning, agriculture, and virtual reality. We found evidence that among those three sectors, the less explored is the VR sector. By setting apart the variables included in the models we analyzed, we identified the most commonly used variables: ANX, CQ, EXP, FC, II, PE, SE, SQ, and SN. Our findings provide evidence that external variables influence in a different manner the two personal beliefs proposed by Davis [388] in the TAM. In our case study, PU's primary determinant was PEOU, followed by SQ, CQ and perceived enjoyment. As for PEOU, it was significantly predicted by SE, followed by PE, and EXP. The seven research categories and the different impacts of external variables demonstrated the context-dependency of technology use. As an acceptance measurement tool, the TAM provides flexibility and accuracy by leaving the doors open for several extensions and applications. The QFD proposed in the present study seems to provide a functional framework for organizing and prioritizing the information.

The adoption of new products and systems is the pinnacle of a successful design process. To increase the likelihood of success, in the last few decades, designers and academics have developed human-centered approaches to better understand what moves users to accept innovation, especially considering the fast pace of development of ICTs and their increasing influence on daily activities [558]. In this sense, to make the most out of the platform, the second part of this study included the validation of the extended TAM version previously proposed for the specific context of FARMER 4.0.

After an initial analysis of the TAM proposed by Davis et al., almost all the relationships were validated except for the effect of PEOU on the attitude (ATT). Findings suggest that the degree to which farmers perceive the system as easy to use (PEOU) will affect their idea about its usefulness (PU). If they perceive the tool as useful (PU), they will have a positive attitude towards it (ATT) and, therefore, will have the intention to use it (BI).

As a technology acceptance measurement tool, the TAM provides flexibility to explore several extensions and find the one that better fits the technology context.

This aspect of the model is advantageous considering the increasing complexity and variety of contexts in which e-learning tools are being applied. Although the initial TAM extension provided a neutral fit for FARMER 4.0, it offers a handy starting point to assess technology acceptance in agriculture, e-learning, and similar sectors.

In our case study, further analysis showed that farmers perceived the tool to be useful (PU) based on the content's quality (CQ). On the other hand, PEOU was influenced by farmers' experience with similar systems (EXP) and their confidence in their skills to explore and use the system and overcome any problem they might face when using the platform (SE). Positive perceptions about the usefulness of the tool (PU) have a positive effect on farmers' attitudes (ATT). Subsequently, ATT stands out as the main driver of intention to use (BI). The PEOU will also reinforce the intention to use FARMER 4.0 (BI). The design and development of future e-learning initiatives should give special attention to the identified factors to increase the likelihood of technology adoption.

Although the sample size of 42 was suitable for the PLS assessment, replicating the analysis with a larger sample size is advisable to confirm and complement the obtained results once all the modules in the five languages are complete. However, infrastructure and resource-related barriers should be overcome to make the most out of the platform. The ultimate benefit extracted from the e-learning tool will also depend on reducing infrastructure and resource limitations. Electricity and internet connectivity should be accessible in rural areas where our target users develop their daily activities. This is especially important, as suggested by Yumashev et al. [559], because a lack of the proper electricity supply can affect the quality of life, reduce the incentives to develop agricultural activities, hamper access to education, and, needless to say, will directly affect the usage of the designed tool. Education institutions can also become key players in reducing resource barriers. They can design and implement strategies aiming to increase learning courses, develop new technological capabilities, gain learning flexibility [383], and make available laboratories and technological tools to allow access to platforms such as FARMER 4.0. Improvements in those directions will increase the incentives to adopt technological tools like e-learning in the agricultural context.

Considering the knowledge gap of technology acceptance in VR innovations and task-level TAM applications, more investigations of those types should be developed. We encourage TAM researchers to provide the existence and validity of relationships along with the effect size. By knowing the variables with a more

significant influence on technology acceptance, innovators' efforts will be better oriented.

Finally, it is crucial to consider the ongoing generational shift in farming activities and how tools like FARMER 4.0 can support it. Sroka et al. [560] found that high levels of education among farmers can accelerate generational changes. In this sense, access to e-learning tools with farming-related content could speed up the transition to the so-called agriculture 4.0, taking advantage of young people's propensity to adopt technological solutions in their daily lives. The increasing interest of young adults in farming-related activities, as evidenced by 45% of respondents with ages between 20 and 35 years, represents an opportunity to further develop e-learning applications in the agricultural sector.

The results of this investigation have been published in two research articles that can be consulted at https://doi.org/10.3390/fi13010007 [561] and https://doi.org/10.3390/app11104672 [182].

7.10 Appendix A. Questionnaire for TAM Validation in the e-Learning Tool Farmer 4.0

The following statements describe the outcomes that people might experience as a result of exploring the Farmer 4.0 learning environment. For each item, indicate whether you agree or disagree, being 1 = strongly disagree; 2 = moderately disagree; 3 = somewhat disagree; 4 = neutral; 5 = somewhat agree; 6 = moderately agree, and 7 = strongly agree.

Appendix A.1. Behavioral Intention

Behavioral Intention refers to your willingness to use the Farmer 4.0 learning environment.

Assuming that I have access to the learning tool:

1. I intend to use the Farmer 4.0 learning environment within the foreseeable future.
2. I will recommend others to use the Farmer 4.0 learning environment to access farming-related content.

3. Overall, I think that using the Farmer 4.0 learning environment is advantageous.

Appendix A.2. Attitude towards Using

This part of the questionnaire explores your general perspective on using the website:

1. In my opinion, it is very desirable and worthwhile to use the Farmer 4.0 learning environment for farming and related purposes.
2. Overall, I have positive feelings toward the Farmer 4.0 learning environment.
3. Overall, I feel that the Farmer 4.0 learning environment is a good and attractive learning environment.

Appendix A.3. Perceived Usefulness

The following questions ask you about the degree to which you believe that using the Farmer 4.0 would enhance your performance in farming and agricultural activities:

1. Using the Farmer 4.0 learning environment would provide service and information very useful in my farming activities.
2. Using the Farmer 4.0 learning environment would improve my performance in farming activities.
3. Overall, I find the Farmer 4.0 learning environment useful.

Appendix A.4. Perceived Ease of Use

The following statements describe your beliefs about the effort you need to do in order to make a good use of the system:

1. I believe using the Farmer 4.0 learning environment would be easy for me.
2. I believe using the Farmer 4.0 learning environment would be clear and understandable.
3. Interacting with the Farmer 4.0 learning environment requires a lot of my mental effort.

Appendix A.5. Anxiety

This part of the questionnaire asks you about the feelings you might experience when using the system:

1. The Farmer 4.0 learning environment is somewhat intimidating to me.
2. Using the Farmer 4.0 learning environment makes me feel uncomfortable.
3. Generally, the use of learning websites stresses me out.

Appendix A.6. Content Quality

The following questions try to identify the degree to which the information provided by Farmer 4.0 fits your needs:

1. The Farmer 4.0 learning environment provides up-to-date information and content that is relevant to my needs and interests.
2. I think that the information I will get from the Farmer 4.0 learning environment is valuable.
3. The Farmer 4.0 learning environment presents the information in an appropriate format.

Appendix A.7. Experience

Now we want to know how previous interactions with similar systems might influence your opinions about the ease of use and usefulness of FARMER 4.0:

1. I have the knowledge and experience necessary to use the Farmer 4.0 learning environment.
2. I feel that my ability to determine the ease of use of the Farmer 4.0 learning environment is determined by my past experiences with similar systems.
3. I feel that my ability to determine the usefulness of the Farmer 4.0 learning environment is determined by my past experiences with similar systems.

Appendix A.8. Facilitating Conditions

The following statements assess the resources and information available to provide help and guidance when using the platform:

1. The Farmer 4.0 learning environment provides helpful guidance in performing tasks.
2. Guidelines and demonstrations on using the Farmer 4.0 learning environment are easily accessible.

3. A specific person or group is available for assistance with any difficulties related with the use of the Farmer 4.0 learning environment.

Appendix A.9. Individual Innovativeness

This part of the survey asks you about how prone you are to try and to adopt new technologies when they appear:

1. Among my peers, I am usually the first to try out new technologies.
2. I like to experiment with new learning systems.
3. I think I would use a learning system for farming related activities, even if I did not know anyone who had done it before.

Appendix A.10. Perceived Enjoyment

The following questions ask you about how pleasant and entertaining you find the e-learning tool:

1. I believe I would find using the Farmer 4.0 learning environment enjoyable.
2. The use of the Farmer 4.0 learning environment arouses my curiosity.
3. My imagination is stimulated by using the Farmer 4.0 learning environment.

Appendix A.11. Self-Efficacy

This part of the questionnaire asks you about your ability to use an unfamiliar software or system:

1. I feel confident finding the information I need using the Farmer 4.0 learning environment.
2. I know I can use the Farmer 4.0 learning environment even if I have not used a system like it before.
3. I am positive that I can overcome any obstacles when using the Farmer 4.0 learning environment.

Appendix A.12. Social Norm

Finally, we want to know the potential role of your personal relationships in the adoption of the FARMER 4.0:

1. People who are important to me would probably suggest the use of the Farmer 4.0 learning environment.
2. Other people beliefs about the Farmer 4.0 learning environment encourage me to use it.
3. I think that most people who are important to me would favor the adoption of the Farmer 4.0 learning environment in my farming activities.

Conclusions

For investigating the role of engagement, this work considered a set of models, methods, and tools within the emotional design context to analyze its features and capabilities to provide appropriate feedback to the design process; in particular, we investigated the Design Thinking methodology, the Technology Acceptance Model, Electroencephalography, and Heart rate as means to understand users' engagement. These methods and tools were applied in selected contexts, such as e-learning, advertising, spaces design, and virtual environments.

User Engagement within Emotional design has been validated as an approach that integrates design visions with appropriate responses from users' perspectives and needs. The design of a product or service must be combined with behavioral and organizational theories to develop an understanding of the user's desires. We have realized that no document in the literature provides a view of the different methods and metrics used to measure user engagement, which entails the challenge of carefully searching and selecting a method from a wide range of possibilities between the various existing methods.

The literature examined more than 1400 studies and derived from three analyses: the first one concerned the self-report methods, the second related to the conceptual definition of the UE through its dimensionalities, and the last one focused on the physiological methods. We noticed that despite their reported limitations, there is a higher prevalence of self-report methods for measuring UE, which opens new possibilities for the incursion of physiological methods to identify in real-time physical metrics and establish if a user is more or less engaged.

In this sense, the first chapter included a review of UE methods and offered insights to facilitate the understanding of the available know-how. This introductory study is a valuable help for any discipline interested in emotional design and can be used as a guide to quickly choose an alternative from all those present in the literature.

In the following phase, this work explored the benefits of User Engagement by deploying DT methodology, a human-focused design approach to increase users' engagement along the innovation process. In the second chapter, we focused our attention on a current need in northern Italy regarding infectious waste management. The DT approach help users to engage with the development of a technology that usually is rejected. This chapter shows a positive case of how to use DT methodology as a framework for new technological designs. With the implementation of DT to develop a technologically-based conceptual design, it was possible to analyze the process holistically, considering the perspectives of the technological and social environment and the opinions of users and stakeholders from the industrial sector, obtaining satisfactory results for the parties interested in this project.

A first approximation to the use of physiological methods was presented in chapter 3; in this case, in collaboration with a Colombian university, we aimed to identify students' cognitive engagement during online lessons using heart rate monitoring. In the development of virtual lessons, one of the main concerns of the professors was to identify activities that encourage the participation of students, capture their attention, and allow the transmission of knowledge. In the development of this research, we found that students feel more comfortable, less pressured, and more willing to participate in a study if factors such as student engagement are measured using a non-self-report method. The results confirm that heart rate can be used as a tool for measuring cognitive student engagement in distance learning, especially if the professor develops an active learning activity since, statistically, the heart rate has a significant variation with respect to the baseline heart rate during the development of these activities.

In view of the potential of physiological methods and the need to deepen emotional research in this field, the following studies were related to exploring EEG as a means for understanding user engagement. The first study objective (4th chapter) was to verify, using an EEG-based index, whether a more interactive advertising might positively influence the participants' purchase intention.

The outcomes show that a more engaging type of advertising influences the UE; indeed, the EEG engagement index was statistically significantly higher when the participants interacted with the Advergames than when they watched the TV commercial. Also, through a quadrant model analysis, the results show that most of the time, a more interactive and engaging type of advertising influence positively the UPI. This first case provided a necessary validation of the EEG-based

engagement indicator, which can be used in line with conventional approaches to minimize partiality from the results.

Considering the obtained results in the first EEG application, and with the ultimate goal of contributing to increasing emotional analysis knowledge, the second EEG research included, besides the engagement, the valence and arousal indicators. In this case, three different Virtual Environments (VEs) with chromatic variations of lighting and four VEs with different form variations were examined in Virtual Reality to investigate whether colors and form variation could elicit an emotional response. The results suggest that the weather and lighting conditions affected the participants' Arousal and that the lack of visible spatial limits could increase task Engagement. Regarding the color lighting, white and yellow have the highest Arousal values, while violet and blue have the lowest. In the case of the Valence, red, yellow, and orange reported the most significant values, while blue was the lowest. In addition, curvilinearity was preferred over angularity forms by means of a higher engagement, similar to blobby forms, in which engagement levels were consistently higher. Outcomes from this study illuminate important aspects of approaching emotional interpretation to design development, particularly with the use of EEG with VR.

Chapter 6 includes the last EEG-based analysis on emotion interpretation; for this case, participants were asked to navigate five VEs explicitly designed to elicit one emotion among happiness, disgust, fear, anger, and sadness. The participants' emotional response navigating the environments was measured in terms of variations of Engagement, Valence, Arousal, and a newly investigated emotional indicator for examining Dominance. It was possible to verify that the EEG was capable of detecting the elicited emotions since the EEG outcomes coincided with the VEs' expected emotions and the SAM's most-rated results. The highest power spectral densities were from theta and beta waves, which means increasing cognitive attention, processing, and elaboration of sensory stimuli was achieved with the VEs. As expected, the most active brain area was the frontal region, the most involved in emotion perception. In addition, in this study, we found in all the VEs a high activation of theta rhythms, which supports the recent findings regarding the VR ability to enhance this particular brain frequency and the upcoming benefits from the creation and analysis of VEs to boost this frequency.

This study concluded the EEG analysis and indicators validation showing positive and promising perspectives in developing systems aimed at comprehending human emotions through biometrics acquisitions.

In addition to the results obtained through physiological methods, it is important to consider the benefits of models specifically designed to measure the acceptance of new developments and explain users' behavior toward technology. Therefore, in the final part of this work, we considered one of the models that have attracted increasing interest in understanding the determinants that shape the users' acceptance of a new system. Thus, a TAM extension was developed and validated in a European agricultural project context (chapter 7). First, a literature review was conducted to identify the most common external variables used in TAM applications, focused on three sectors: e-learning, agriculture, and virtual reality. We identified the most commonly used variables: anxiety, content quality, experience, facilitating conditions, individual innovativeness, perceived enjoyment, self-efficacy, system quality, and social norm. Subsequently, we assessed the technology acceptance by validating the extended TAM version previously proposed. Further analysis showed that farmers perceived the tool as useful based on the content's quality. The perception of ease of use was influenced by farmers' experience with similar systems and their self-efficacy when using the platform. Positive perceptions about the tool's usefulness positively affect farmers' attitudes. Subsequently, the users' attitude stands out as the primary driver of intention to use.

This work demonstrates the possibility of obtaining feasible results based on the analysis of users' behavior. Methodologies and models, such as DT and TAM, are characterized by their focus on the users and their capacity to include different stakeholders. Due to their holistic and iterative characteristics, from a business point of view, these methodologies allow for repeatability across different industrial sectors. They can be applied compatibly with project execution while keeping budgets contained. By considering customers' needs from the early stages of the development process, the results can be reflected in a better perception of the products and services offered and increased engagement of all stakeholders.

On the other hand, the previous studies are making considerable progress on physiological technics, analyzing the physical user responses to a stimulus, and obtaining a reliable engagement value. The findings demonstrate that the inclusion of physiological characteristics provides information that allows the researcher to determine whether self-report results are trustworthy and representative.

Throughout this work, each investigation on its own contributed to the overall goal of this work; the development of each chapter following a concrete approach allowed us to gain more experience and obtain valuable results for generating knowledge regarding user engagement within emotional design.

Some observations can be drawn from the obtained findings, especially in light of potential future developments.

There are no standardized scales regarding user engagement levels since the measurements depend highly on the conditions under which the studies are carried out. Consequently, standardized scales are still a research gap.

The best method to use will depend on many factors. On the one hand, self-reported practices have been in the UE context for more time, and it is usual to find validated instruments for specific fields; however, their dependency on the participants' answers could alter the ground truth; in this sense, physiological methods play an important role by adding a comparable data.

It is also essential to consider resource availability, budget, time, and experience. Physiological approaches require more expensive equipment than self-reports, and the researchers must undergo a training phase to gather and analyze valid data. Fortunately, physiological technology is becoming more approachable and reasonably priced.

We recognize the implications of working with large sample groups in physiological experiments; however, to ensure that emotional responses are reflected accurately, we encourage future studies to incorporate larger interest groups that can further validate the results.

Regarding a specific EEG feature, emotional EEG-based indices have been validated primarily in clinical settings; this implies possibilities for future research in the creation of indicators explicitly developed for the study of emotions. A case of particular interest is the dominance indicator, whose results in the literature are quite limited. Lastly, using more immersive VRs such as the CAVE system, validating with systematic comparison can further expand our findings.

In conclusion, we can state that, as well as the interest in understanding the users' inner perceptions is increasingly growing, user engagement emerges as an important element of emotional design, as it encourages users to interact with a product in a meaningful way. Through engagement, the user forms an emotional connection with the product, which can be used to analyze their behavior and attitudes toward it. Also, engagement facilitates a sense of belonging and investment in the product, which is essential for emotional design to be effective. As such, engagement is a key factor in creating emotional experiences that are both memorable and meaningful to users. Its diverse implementation possibilities make

it a flexible parameter with an excellent cost-benefit ratio. In view of the positive outcomes, this work can be considered a potential foundation for future applications that wish to include user engagement as a criterion in their research.

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