Towards Emotionally and Motivationally Aware Intelligent Systems: A Systematic Literature Review

A PRISMA Systematic Literature Review

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A Thesis Submitted to EEMCS Faculty Delft University of Technology,
In Partial Fulfilment of the Requirements
For the Bachelor of Computer Science and Engineering
June 22, 2025

Abstract

Recent developments in Artificial Intelligence offer new possibilities for the development of systems which adapt to human motivation or emotion. These can have a variety of applications such as making therapy more accessible or boosting student motivation or engagement. In order to gain an overview these applications, of adaption strategies and inputs are used and challenges researchers are facing during development, a Systematic Literature Review was conducted. The review follows PRISMA guidelines and includes from *Scopus*, *Web of Science* and *IEEE Explore*. Due to time limitations, only papers published in 2024 and 2025 were considered. The final review includes 139 papers, out of which only 6 target motivation. 46 were chatbots, and 53 were recommendation systems. Researchers primarily struggled with the interpretation of complex emotions, and the need for more adaptation options. Lastly, a strong need for extensive user testing and comprehensive data privacy measures was identified.

1 Introduction

As modern technology, specifically computers and the intelligent systems that run on these, become an ever-more ubiquitous part of our lives, the way we interact with these and the way they respond to our interactions is also increasingly important. We have reached a point where we can largely model computer systems to accommodate our needs, instead of us having to "put up" with the limitations imposed by computers [1]. Newly available resources, such as Artificial Intelligence (AI), have led to significant advancements in the fields of human emotion and motivation recognition [2], as well as user modeling [3].

This opens up a new horizon of possibilities for Human-Centered AI (HCAI) systems that adapt to human emotional and motivational states to improve user experience and enhance their effectiveness. Some relevant examples of human-centered intelligent systems include: electronic learning environments that monitor a student's motivation levels and try to adapt their teaching mechanisms to fill in gaps or make learning more engaging [4–6]; games which adjust characteristics such as difficulty in order to offer a more enjoyable experience [7]; adaptive user interfaces which can be used to reduce the stress or or help maintain the focus of drivers [8] or pilots [9]; chat bots that promote healthier lifestyles for elders [10] or aid people with their mental health [11].

However, as with any emerging field of research, there are many questions that remain unanswered, such as which emotions are most relevant to model [1, 12], to which emotions and when should a system adapt its behavior [1, 12], is it possible to create a set of guidelines for developing affectively intelligent systems [12].

Additionally, there are few recent surveys that offer a comprehensive overview of the aforementioned topics, with the exception of some domain-specific surveys as discussed in 1.2. Thus, this paper aims to bridge this gap by performing a survey of recent implementations and designs. The main research question is: **how do intelligent systems acquire and use information related to user motivation and emotion to enable adaptive behavior?** To aid in answering this question, 5 sub-questions have been formulated, as presented in table 1. The questions were given by the project description.

The results of this survey will aid Computer Science researchers in the development of future intelligent systems. It may identify further research gaps, as well as offer guidance on what principles have worked so far. Furthermore, it might help psychologists and social scientists by offering an insight into what emotion/motivation modeling systems might be worth developing further, or might provide them with new mechanisms to study human behavior.

This paper is structured as follows. Subsections 1.1 and 1.2 provide more background on this study's definition of motivation, emotion and intelligent systems, as well as provide and overview of existing surveys and the specific contributions this study brings. Section 2 describes in detail the steps taken in conducting the survey. Afterwards, section 3 discusses the results, followed by the author's interpretation of these in section 4. Section 5 presents the limitations and potential bias of the study. Finally, section 6 summarizes the main conclusions of the research and provides insights into possible future work.

Sub-question	Motivation
SQ1: What forms of information related to emotion and/or motivation has HCAI research used for adaptation of intelligent systems?	There are many ways emotion and motivation could be measured be sensed and modeled by a computer. It is interesting to see what representation schemes work in practice.
SQ2: For what objectives has this information been used?	Possible objectives could be to enhance the efficiency of a system, to induce a particular state in a user, or make the user experience more enjoyable. Looking at this may open the avenue to potential new uses, or show situations in which HCAI may not be adequate.
SQ3a: How has this information been used in the adaptation of intelligent systems?	This refers to the adaptation process. What emotional or motivational states trigger adaptations? What kind of adaptations and when? Knowing this is useful for determining what system designs work, and what has yet to be tried.
SQ3b: Are there any trends or patterns observable regarding the adaptation of intelligent systems?	Any trend or pattern may lead the path to the creation of guidelines that developers might use for the design and development of HCAI systems.
SQ4: In which application domains have these systems been used?	There may be application domains to which HCAI is more suited, there may domains that are underexplored.
SQ5a: What challenges and trends exist in recent developments?	Knowing this may reveal aspects that require further research.
SQ5b: Are there any trends or patterns observable with respect to challenges and trends?	It would be good to identify what researchers have been mostly struggling with, to guide future research.

Table 1: Sub-questions that will help answer the main research question and the motivation behind them.

1.1 Background

Throughout this paper, an intelligent system is defined as a system that is capable of perceiving its environment and interacting with it, and other intelligent agents, as well as exhibiting "rational thinking" and being able to take decisions that "maximize the success of its tasks" [13]. Intelligent systems, or artificial intelligence, are commonly understood to use some form of Machine Learning (ML), however, that is not a requirement for the systems studied in this paper. Systems that adapt on the basis of a adaptation loop [14] are also considered. Moreover, this paper only considers systems that are human-centered. Namely, systems that perceive information about a user, and then adapt their behavior based on that information. To qualify as human-centered, it is also important for these systems and their adaptation strategies to be, at least to some degree, explainable [15]. If the adaptation strategy is unclear or left entirely up to a ML algorithm, it becomes difficult to extract information about a system, but also for its users to feel in control of it. Figure 1 presents a schematic of the general architecture of the systems studied.

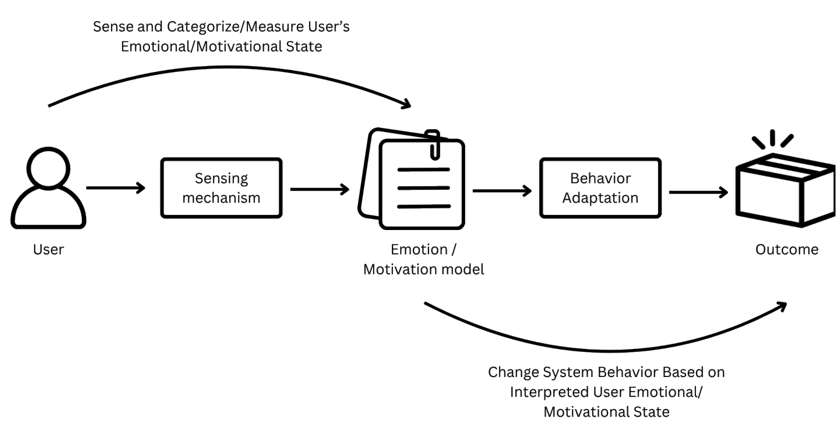

Figure 1: Conceptual Model of Motivationally or Emotionally Aware Intelligent Systems

Furthermore, some discussion on the definitions of emotion and motivation is necessary. While there is no consensus on the definition of emotion [16, 17], this paper will perceive it as an intense, short-lived mental-physical state that is caused or directed at an object [18]. This is an attempt to distinguish emotions from other affective processes such as moods, which often are not aimed at a specific object and have a longer duration [18]. Even so, there are a multitude of emotion classification models. A recent survey [2] identifies two predominant emotion representation schemes: discrete emotion models (for example: Ekman's basic 6 [19], Plutchik's wheel of emotions [20]), and dimensional emotion models (for example: Pleasure-Arousal-Dominance [21]).

Similarly, motivation is generally understood to be process of setting and achieving goals [22]. It is perhaps an even more elusive process than emotion, as it cannot be directly observed, for example by looking at facial expressions, and must be inferred from context [23]. Furthermore, it is also challenging to model and measure, as there are many definitions [24] and theories regarding different types of motivations [25]. As such, computer systems often have complex user models to represent motivation, which are usually context specific (e.g. player models [26, 27]).

Motivation and emotion are considered together in this study as user emotion often plays an important role in the creation of a user's motivation profile. Moreover, cognitive-appraisal theory states that emotions are "reactions to the status of everyday goals" [28] (p. 820), so emotion and motivation are processes that influence each other.

1.2 Related Work

Similar surveys have been conducted, but usually have a narrower scope. For example, [29] analyzes sensing mechanisms, use cases and challenges of emotionally adaptive intelligent systems, but only in the context of autonomous vehicles. [30] looks at emotion sensing and classification for intelligent tutoring systems, but does not provide detailed overview adaptation strategies. Similarly, [31] looks at the general structure and characteristics of chat bots, and [32] analyzes user modeling and adaptation from the perspective of HRI. This survey distinguishes itself by trying to provide an overview of various types of emotionally intelligent systems, and across various domains, in order to find more general patterns.

A survey published in 2021 [33] provides a comprehensive overview of most aspects of intelligent systems considered in this survey: emotion recognition techniques, application domains, what parts of systems were adapted. Nevertheless, with the advancements made in the area of Machine Learning in recent years, especially considering the introduction of generative pre-trained transformers (GPT) by OpenAI in 2018 and the release of ChatGPT [1] to the public in 2022, new techniques for emotion recognition and modeling may have been developed. Furthermore, this study aims to look at the specifics of the adaptation strategies, the challenges and limitations of these, and systems that also consider motivational states, not only emotional states.

2 Methodology

This review follows PRISMA [34] guidelines for reporting, ensuring that the process is transparent and reproducible. The review was conducted in a systematic manner, following the steps outlined in [35]. The first steps included refining the research questions and performing scoping searches. This resulted in a set of 12 papers which were used to establish the eligibility criteria, described in 2.1, and to define the search strategy, described in 2.3. After establishing these and the search engines to be used, presented in 2.2, the papers obtained were subjected to multiple filtering steps, presented in 2.4. Finally, the data extraction criteria and process were defined and described in 2.5. This process was carried out by one researcher.

[1] https://openai.com/chatgpt/overview/

2.1 Eligibility Criteria

In a systematic literature review (SLR), inclusion and exclusion criteria guide the selection process. It is important for these to be clearly defined, so as to provide a reproducible structure and facilitate the selection process. The criteria were defined such that all information necessary to answer the research questions would be present in the paper, and the system matches the conceptual model described in Section 1.1.

Inclusion Criteria

- Studies that present implementations or designs of emotionally or motivationally intelligent systems, as described in Section 1.1;
- Studies in English;
- Conference papers and journal articles.

Exclusion Criteria

- Literature or conference reviews *(this would prevent accurate data extraction)*;
- Papers that are not in English;
- Studies that focus only on the effectiveness/impact/challenges/design of systems, without describing the system used in detail;
- Studies that enhance/improve/change aspects about existing systems. *(this would prevent from understanding the concrete design behind a system)*;
- Systems or studies of systems that are not computer-based *(this will excluded systems/frameworks used in fields such as psychology, education, etc.)*;
- Systems or studies of systems that do not measure or model information about a user's emotional or motivational state *(this will exclude systems that strictly mimic emotion/motivation, do not focus on a human user, or discuss other cognitive-affective processes)*;
- Systems or studies of systems that do not adapt their behavior based on the user's emotional or motivational state, or do not provide clear indication as to how the adaptation may be done *(this will exclude non-adaptive systems, systems that adapt based on other input, or systems that strictly focus on the state recognition/modeling aspect)*;

2.2 Search Engines

To perform the survey, the following research databases were chosen: Scopus [2], Web of Science (Core Collection) [3], IEEE Explore [4]. All of these databases provide advanced search functionality, suited for carrying out a literature survey. The first two were chosen because they are large, interdisciplinary databases. The latter was chosen as it includes more computer science focused research. Other databases were excluded due their lack of search functionality or thematic.

2.3 Search Strategy

The set of 12 base papers was formed by performing scoping searches and snowballing. The scoping searches were done by querying Scopus, Web of Science and Google Scholar with simplified versions of the final query, such as "emotion AND intelligent system". Snowballing is a technique by which papers are found by looking through the reference list of other relevant papers [TODO]. This study primarily looked at the references of [1] and [26].

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

The base set of papers was used to define key concepts that represent important aspects of the papers that this survey aimed to find. These concepts, along with some of the synonyms that were used in query construction are presented in Table 2. For a full version of the final queries used to search the databases, please consult Appendix B. The terms relating to emotion and motivation were searched with an "OR", as the study includes systems that consider either. Additionally, terms relating to surveys were included with a "NOT", so as to exclude these early on.

Key Concept	**Motivation**	**Synonyms**
emotion	Targeted systems must adapt based on emotional information.	emotional state*, happy, sad, fear, anger, angry, disgust, surprise, stress, anxiety
motivation	Targeted systems must adapt based on motivational information.	motivational state*, extrinsic, intrinsic, goal-oriented, self-determination, self-efficacy, curiosity
user	The system must take into account specifically a user's state, not for example computer/robot emotions or motivation.	person, player, student, driver, pilot, patient
recognition	In order to be able to adapt based on emotion/motivation, a system must also be able to recognize these.	assess*, collect*, recogni*, detect*, classification, profile, type
adaptation	Targeted systems must present some form of adaptive behavior based on the user's state.	adapt*, respon*, interactive, personaliz*, personalis*, react*, feedback
intelligent system	This acts as a limiting search term, in order to constrain results to computer systems, as there are many frameworks that have all of the above aspects, but are based in psychology, education, etc.	intelligent system, adaptive system, affective computing, human-robot interaction, chatbot, recommender system, adaptive user interface
review	Exclude literature surveys and reviews from the start, if possible.	survey, compar*

Table 2: List of key concepts, their motivations and part of the synonyms used for query construction

Feasibility Constraints

This study was conducted over a period of 9 weeks, by a single researcher. Seeing that HCAI is currently a highly active field of research, it was necessary to introduce additional constraints in order to make the survey feasible within the allotted time frame. As such, only papers from 2024 until 18 May 2025 were considered. This time constraint was applied using the time filters from the research databases used, before the selection process.

2.4 Selection Process & Search Results

The papers produced by the search queries were introduced in a reference management system. These were then filtered out in 3 steps. First, the papers were screened only by title. This phase quickly eliminated papers that were not related to computer systems, and studies that focused only on developing datasets or recognition models. Second, that papers were screened by abstract. The reasons for exclusion were recorded, to aid in the analysis part. Third, the full text versions of the remaining papers were obtained, and were again screened using the eligibility criteria. This ensures that the remaining papers contain all the information necessary to answer the research questions. Additionally, if a paper fit multiple exclusion criteria, it was counted for both. Figure 2 presents the number of papers eliminated at each step. In the end, 139 papers were included in the review.

2.5 Data Extraction & Synthesis

Before analysis can be done on the results, all relevant data from the papers remaining after filtering must be extracted. Specific data extraction points were defined, and overview of these are presented in Table 3 where "user state" specifically refers to a user's emotional or motivational state. All of the extracted data was stored an Excel table, which was then used to synthesize and group papers

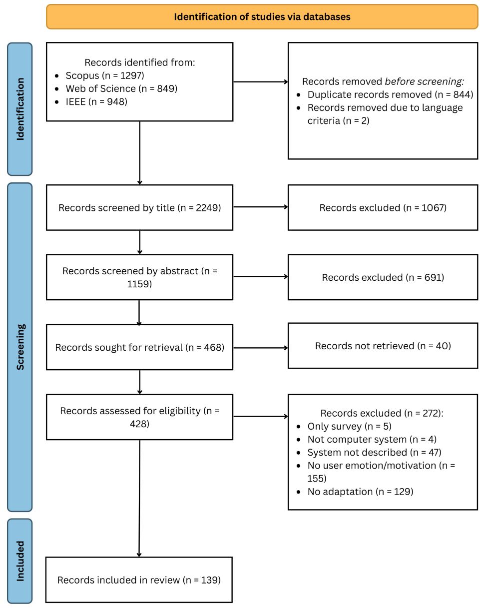

Figure 2: PRISMA Flow Diagram

according to the research questions. The groupings were done by the author and are explained in detail in the corresponding results section.

Data point	**Subquestion(s)**
Publication year	SQ5a, SQ5b
Country of researcher's universities	SQ5a
Do they use unimodal or multimodal input for measuring user state?	SQ1
Do they use visible, or invisible inputs for measuring user state?	SQ1
Are the methods for measuring user state intrusive or not intrusive?	SQ1
What sensors and recognition techniques do they use for measuring user state?	SQ1
Which emotion/motivation representation model(s) to they use?	SQ1, SQ3a, SQ3b
What system element do they adapt based on user state (UI, difficulty level, recommended content, etc.)?	SQ3a, SQ3b
Does the system continuously learn about the user?	SQ3a, SQ3b
What are the objectives of the adaptations within the system?	SQ2
Application domain	SQ4
What challenges, limitations and directions for future research are proposed?	SQ5a

Table 3: Data extraction points

3 Results

This section presents the findings of this review [10, 11, 36–172], structured roughly according to the research questions. Subsections 3.1, 3.2 and 3.3 present the inputs and recognition techniques, emotion and motivation models used respectively. Then, the identified application domains are presented in Subsection 3.4, followed by common system objectives in Subsection 3.5. Afterwards, an analysis of adaptation strategies and their patterns is presented in Subsection 3.6, ending with the description of challenges researchers faced in Subsection 3.7.

3.1 Recognition Techniques

As discussed in Section 1.1, a core aspect of the intelligent systems studied is the capacity to recognize a user's emotion or motivation. Computer systems do this via various sensors such as cameras, microphones, etc. Various techniques, such as signal processing and Machine Learning (ML), are used to analyze these inputs which are subsequently used for modeling emotions or motivations. Table 4 presents the techniques identified in this study. Inputs have been categorized as visible (VI) or invisible (II), based on what humans can naturally perceive, as per the description in [33].

Recognition Technique	Emotion Recognition	Num.	Motivation Recognition	Num.
Facial Feature Analysis	[11, 36–39, 47–49, 51, 53, 55–58, 63, 67, 70, 71, 74, 77, 79, 81–90, 94–96, 98, 102, 104, 105, 107, 110, 111, 113, 114, 117–120, 122, 129, 131, 133–139, 141–145, 147, 148, 154–158, 160, 161, 165, 167, 170, 172]	76		0
Speech Feature Analysis	[37–39, 45, 47, 49, 51, 53, 55, 60, 66, 74–76, 78, 80, 90, 92, 94, 95, 102, 106, 113, 114, 118, 124, 131, 140, 147, 148, 153, 158, 163, 167]	34		0
Natural Language Processing	[11, 38–40, 42, 43, 45–47, 51–54, 59–62, 64, 66, 68, 69, 71, 73, 74, 76, 80, 92, 94–102, 106, 107, 109, 111, 113–116, 118, 121, 123–128, 131, 132, 137, 146–148, 151, 152, 157, 159, 162, 166–169, 171]	68	[10]	1
EEG	[42, 44, 50, 63, 72, 75, 93, 112, 149]	8		0
HR	[63, 71, 75, 122, 129, 150, 167]	7		0
GSR	[71, 122, 150, 167]	4		0
Gaze Tracking	[37, 60, 87]	3		0
Other	[38, 52, 57, 58, 65, 66, 75, 82, 87, 90, 106, 113, 117, 122, 129, 140, 167]	20	[41, 91, 103, 108, 130]	5

Table 4: Systems sorted by recognition techniques.

In terms of visible inputs, the two most popular techniques are facial feature analysis and Natural Language Processing (NLP). Facial analysis is typically done by scanning images or camera feeds, while NLP involves text processing. Interestingly, some systems use speech-to-text before performing NLP. Speech features such as pitch, tone, volume are also widely used to determine user state. Their analysis is typically done in conjunction with NLP, as only 3 systems do it exclusively [78, 153, 163].

Other techniques for visible inputs include gaze tracking, head pose estimation [57], body posture and movement analysis [113, 140], hand gesture analysis [117], grip strength [129] and pressure analysis [106, 164]. Systems also use mouse and keyboard activity [38], clicks and screen taps [87], and user activity, such as what actions a player takes in a game [41], self-report questionnaires before and after an activity [103], how much a time a student spends on an exercise [108], or simply direct user feedback on whether they like the shown content [58, 90].

As for invisible inputs, various physiological signals are used. The most popular are Electro-Encephalogram (EEG) signals, which represent brain activity, and are measured using VR headsets or dedicated EEG headsets. Other techniques used include Heart Rate (HR), Galvanic Skin Response (GSR), Electro-Cardiogram (ECG) signals and pulse [75, 122] and blood oxygen levels [167].

It is interesting to note that 4 systems [52, 65, 66, 90], classed under "Other" in Table 4, did not clearly indicate what forms of input or which recognition techniques were used.

Additionally, out of the 133 systems that adapt based on emotion, 87 are unimodal (U), while 46 are multimodal (M), using more than one input to identify emotions. For motivation, only 2 out of 6 are multimodal. Systems can also be categorized based the intrusiveness of the sensors used. This is similar to the categorization of Wang et. al [2], however, devices that a user would intentionally use everyday life, such as a smartwatches or VR headsets were classed as non-intrusive, despite having to be worn. These insights are visually quantified in Figure 3.

3.2 Emotion Representation Models

As discussed in Section 1.1, there are two main types of emotion classification models: categorical and discrete. However, some systems is this study combination both. An overview of which model systems

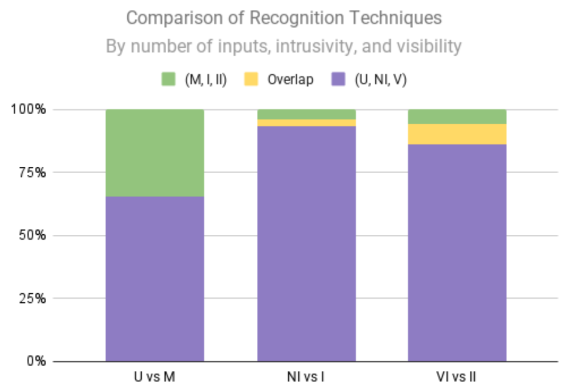

Figure 3: Comparison of Aspects of Recognition Techniques.

use is given in Table 5 and in Figure 4.

Emotion Model	Num.	Papers
Categorical	81	[11, 36, 39, 43–45, 48, 51, 53, 55, 56, 58, 59, 64, 68–72, 77, 78, 81–86, 88, 89, 92, 98–101, 104, 107, 109–111, 114, 119–122, 125, 128, 129, 131, 132, 135–139, 141–146, 148, 151–159, 162–168, 170–172]
Dimensional	8	[42, 62, 63, 74, 93–95, 123]
Categorical and Dimensional	8	[38, 50, 57, 76, 90, 140, 150, 161]
Unclear	35	[37, 40, 47, 49, 52, 54, 60, 65–67, 73, 75, 79, 80, 87, 96, 97, 102, 105, 106, 112, 113, 115–118, 124, 126, 127, 133, 134, 147, 149, 160, 169]

Table 5: Systems sorted by type of type of emotion classification model.

For systems using categorical models, it was observed that not all explicitly state the full list of the emotions they classify. Furthermore, some only categorize emotions as positive or negative, and others do this on top of the normal categorization. These insights are presented in Table 6. Interestingly, most papers do not explicitly reference psychological theory behind the emotions chosen.

Categorical System Subdivision	Num.	Papers
Clear categories	58	[36, 43, 44, 46, 48, 51, 55, 56, 58, 59, 68–70, 72, 78, 81–86, 88, 89, 98, 100, 104, 107, 110, 111, 114, 120, 122, 128, 129, 135, 138, 139, 141–146, 148, 152–157, 159, 164–166, 168, 171–173]
Only positive and negative	6	[64, 132, 151, 162, 163, 170]
Mix	6	[101, 121, 131, 136, 137, 167]
Unclear	11	[11, 45, 53, 71, 77, 92, 99, 109, 119, 125, 158]

Table 6: Categorical models further subdivided.

Figure 5 presents the emotions identified by the systems that provided a full list (including systems that mixed these with positive and negative categories). It is important to mention that this review included depression and stress when contextualized as emotions, as user reactions. As depression and stress can be considered broader affective categories, these were not the focus of this review.

In terms of dimensional models, 6 out of the 8 systems use the valence-arousal model (VA), a system uses only valence [123], and another uses the valence-arousal-dominance model [94]. Systems that used mixed categorical and dimensional models combine VA with predefined emotion categories. One standout is a system that uses the Hourglass Emotion model [174], alongside VA [38]. Lastly, a

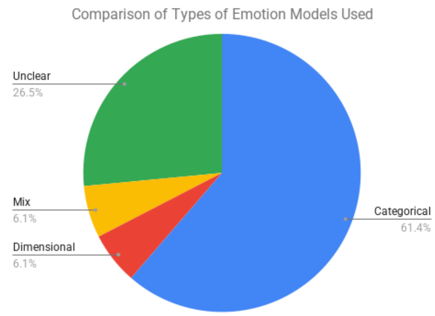

Figure 4: Comparison of Categorical vs. Discrete Emotion Models.

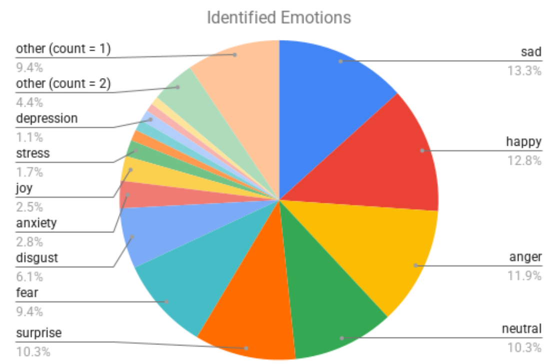

Figure 5: Percentage of Emotions Identified.

large number of systems were classified as "Unclear". While 18 of these systems mentioned the usage of ML, 17 did not provide any indication of the models used.

3.3 Motivation Representation Schemes

No pattern for motivation modeling was found. Two systems [10, 108] did not provide a description of the modeling aspect, and another simply classed motivation as high or low [103]. The systems that stand out are the ones whose model is based on what motivates users. Nikolopoulos [41] used the Hexad Player Model [27], which classifies players by the activities they want to do in a game, such as socializing or rewards. For Rostami [91], a user can be motivated to eat a dish by trends, aesthetics, desire to try new things, desire to eat healthy, or a liking for niche things. Curiosity was also included as measure of motivation, as per Fu [130], as it is factor which drives people to engage with certain items or in various activities.

3.4 Application domains

The identified domains are presented in Table 7. In this context, healthcare is understood as systems that aid with a user's physical or mental well-being. As a subdomain, mental well-being encompasses systems that target mental health disorders, but also systems that offer therapeutic benefits such as meditation, mood regulation, or simply emotional support. One standout is a food recommendation system [91]. Despite the paper not explicitly mentioning health as the goal, it did point out the necessity of the system to not recommend unhealthy food repeatedly.

Under the entertainment domain were classed systems that typically are related to entertainment, despite this not always being explicitly stated. This includes music, video, and movie recommendation systems, games, streaming, storytelling platform. Importantly, not all music recommendation systems were classed as entertainment. If they explicitly mentioned therapeutic benefits, then the systems were put in the mental well-being category. If alongside this, they also mentioned other goals such as music discovery, they were classed as both entertainment and mental well-being.

If systems aim to teach users or assist with learning, then they are counted as education. Systems tasked with improving the mental well-being of students are classed in the respective category, and not in the education domain as they are not primarily concerned with learning assistance. Lastly, marketing covers systems that offer benefits to companies. This includes boosting brand connection or selling items.

All of the above domains aim to improve the way humans interact with technology. However, a separate HCI domain was included for systems which specified they could be used in multiple domains, or which were not designed for a specific domain. Human-Robot Interaction (HRI) was included as a notable sub-domain, referring to the interaction with robotic platforms.

Nikolopoulos's system [41] stands out as not fitting in any of the aforementioned domains. This system aims to improve the motivational impact of gamification elements, in non-game environments. Thus, it does not focus specifically on improving HCI, and uses computers only as a tool to achieve a larger goal.

Application Domain	Sub-domain (if applicable)	Num.	Papers
Healthcare	Mental Well-being	47	[11, 42, 45, 49, 50, 52, 63–65, 68–70, 72, 73, 75, 81, 85, 93, 94, 97, 99, 100, 107, 109, 111, 112, 115, 116, 118, 121, 123, 125–128, 132, 138, 145–147, 149, 152, 155, 159, 162, 169, 172]
	Elderly Care	3	[10, 39, 74]
	Physical rehabilitation	3	[44, 150, 165]
		1	[103, 166]
Entertainment		43	[36, 48, 51, 56, 58, 60, 71, 77, 80–86, 88, 89, 92, 101, 102, 104, 105, 110, 111, 117, 120, 133–136, 138–140, 143, 144, 146, 154, 155, 160, 163, 175]
Education		12	[38, 54, 55, 57, 67, 78, 79, 108, 122, 148, 158, 168]
Marketing		4	[46, 61, 66, 167]
HCI	HRI	4	[37, 95, 137, 164]
HCI		24	[40, 43, 47, 53, 59, 62, 76, 87, 90, 91, 96, 98, 106, 113, 114, 119, 130, 131, 151, 157, 161, 170, 171]
Other		1	[41]

Table 7: Systems sorted by application domains.

3.5 System Objectives

System objectives vary widely, and would be too granular to represent in a table. As such, they have been grouped by application domain, and an overview is presented in Figure 6. A detailed list of papers and the specific objectives they have is presented in Appendix C.

In healthcare, the most popular goals are helping users regulate emotions, offering therapeutic guidance and advice, or simply providing emotional support and companionship. Other goals relate to improving availability: combating the lack of trained personnel (Scalability), the need for constant support (Availability), helping people overcome stigma when getting help (Stigma), and simply improving comfort (Ease of use). Notably, some papers emphasize aiding standard therapy methods, and not replace these.

When it comes to entertainment, the most notable goals are helping users navigate the large digital landscape, discover new media, feeling more connected to the content they consume. Many simply aim to offer a personalized experience, without elaboration. Some outliers include reducing the cost of animation, keeping streamers and chats engaged, eliminating need for manual reviews and increasing user retention.

Educational systems commonly aim to increase student engagement and motivation. While many mention improving effectiveness, few define how it is measured. Some highlight goals like offering 24/7 support or enabling more personalized learning. Marketing systems aim to boost brand connection and customer satisfaction to enhance business profits. In the HCI domain the most prevalent goal is to simply improve user experience or provide more natural, human-like interaction. Other interesting HCI objectives are making driving safer, assisting humans with physical tasks, or improving UI accessibility.

Some systems fall outside these domains, often suggesting broad or future use case. For example, a recommendation system that can be trained on any dataset of items [130]. Standouts from the "Other" category are helping families in stressful home situations [106], studying the impact of empathy in HCI, and one study with no stated goal [140].

3.6 Adaptation Strategies & System Types

To understand how systems use emotion or motivation data, they were classified by type (see Table 8.

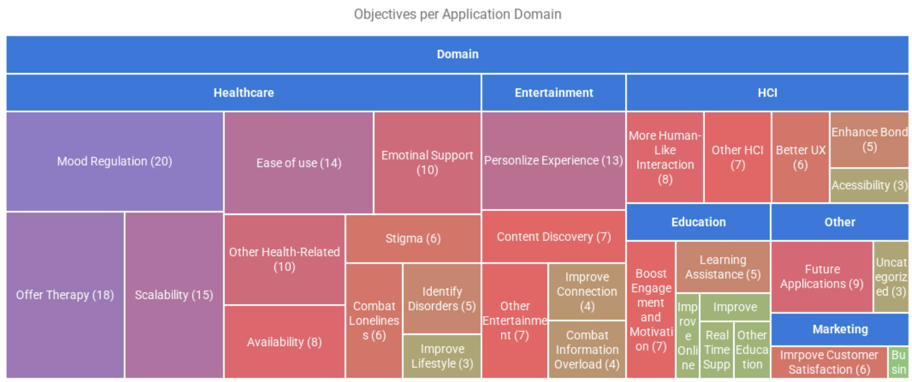

Figure 6: Graph of Objectives Sorted by Application Domains.

By far, the two main system types are Social Agents (SAs) (42%) and Recommendation Systems (RSs) (38%). SAs facilitate conversations or social interactions, and include chatbots which adapt text or speech replies, virtual agents (VAs) which also adapt a virtual avatar's facial expressions and gestures. Some standouts from the "Other" category are: storytelling robots [58, 160] adapting the speed, tone and type of story; a dancing robot companion [72]; a neuro-rehabilitation robot and VA combination [165].

In terms of RSs, they have been categorized based on the type of content they suggest. The recommendations are typically made via a web or mobile application, however, some provide suggestions through a conversational interface and received their own category. "Other" RSs include suggestions of gamification elements [41], food [91], physical activities [166, 176], art activities [167].

Games adapt elements such as difficulty, quests, character tone, and the two driving systems stand out. One features pneumatic paw pads on a steering wheel which alert or calm the driver [129], the other switches control of the car to an autonomous system when a user is depressed [156]. Learning platforms adapt assignments, gamification elements, tone of feedback, usually in combination. The adaptive graphical elements category includes VR landscapes which change visual elements or background music [50, 149, 172], a desktop environment which changes color themes and wallpapers [119], or web platforms which change layouts and themes [87, 161].

Lastly, the "Other" category includes content generators [80, 102], and an adaptive exoskeleton that adapts assistance levels based on a user's emotional valence. [150].

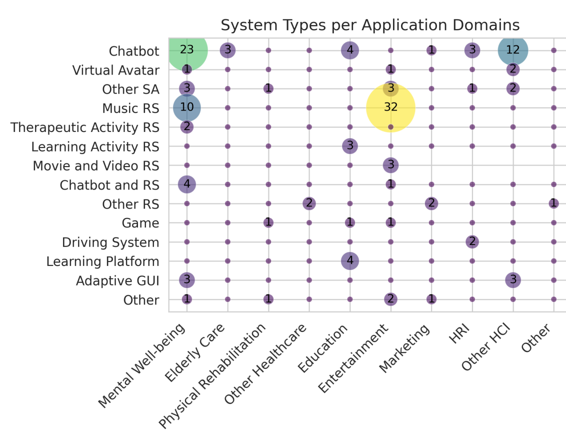

Figure 7: System types per application domains.

System Type	System-Subtype	Num.	Papers
Social Agent	Chatbot	46	[10, 37, 39, 40, 45–47, 49, 54, 55, 59, 62, 64, 65, 68–70, 73–76, 94–98, 100, 113–116, 121, 124–128, 137, 151, 152, 158, 159, 168, 169]
	Virtual Avatar	4	[43, 53, 60, 109]
	Other	8	[51, 58, 72, 93, 106, 118, 160, 164, 165, 170]
Recommendation system	Music	35	[36, 52, 56, 63, 71, 77, 81–83, 85, 86, 88, 89, 92, 101, 104, 105, 107, 110, 112, 117, 120, 134, 138–140, 142–146, 153–155, 163, 175]
	Therapy Activity	2	[99, 147]
	Learning Related	3	[38, 57, 78]
	Movies and Videos	3	[133, 135, 136]
	Other	10	[41, 61, 90, 91, 103, 130, 157, 166, 167, 171]
Chatbot and Recommendation System		5	[11, 42, 111, 123, 132]
Game		3	[44, 48, 122]
Driving System		2	[129, 156]
Learning Platform		4	[67, 79, 108, 148]
Adaptive Graphical Elements		6	[50, 87, 119, 149, 161, 172]
Other		4	[66, 80, 102, 150]

Table 8: System types.

Patterns Regarding Adaptation & System Types

Systems have been classified as offering continuous (47, or 35%) or non-continuous adaptation (92, or 66%). Continuous adaptation has been defined as systems which learn about a particular user, taking into account historic data and previous interactions when adapting. The adaptation of non-continuous systems depends only on the current user state.

Figure 7 showcases the number of system types in each application domain. We can see that mental well-being chatbots and music RSs are the most prevalent, with other types not exhibiting a pattern across application domains.

3.7 Challenges and Limitations of Studied Systems

Challenges and limitations were extracted based on author statements and future work, and are summarized in Table 9. Notably, 22 papers (16%) did not mention any.

A common issue was the need for more diverse or larger datasets to improve user state recognition, with one study highlighting the risk of bias [95]. Several systems struggled with detecting rapid or subtle emotional changes [93, 94, 141, 163] or suffered from underrepresented emotions in training data. Others noted limitations in dark or noisy environments [90, 141, 144, 161], and one game system mentioned that users could fake expressions to cheat [122].

In terms of adaptation, many systems cited the need for broader content options: more songs [107, 120, 128, 132, 140, 142, 153, 155, 164], chatbot responses [10, 47, 54, 59, 64, 71, 94, 98, 115, 116, 121, 162], robot movements [93], and animations [53]. Several papers noted the absence of continuous learning, while others that included it raised concerns about cold start issues. One paper stressed the need to continuously update chatbot datasets with current psychological data [128].

Many systems also emphasized limited user testing, including needing real-world conditions [58, 129], bigger sample sizes [57, 118, 122, 129, 155, 165, 170], and long-term studies [108].

Patterns Regarding Challenges & Limitations

Of the 139 systems, 29 (21%) did not mention any testing method; 5 of these were not implemented, explaining the omission. 51 (37%) reported user testing or feedback, but only 13 referenced ethics

System Aspect	Challenges	Num.	Papers
Recognition and modeling	Need for more advanced NLP techniques and more language support	5	[58, 92, 100, 111, 160]
Recognition and modeling	Unreliable Signals	3	[42, 61, 167]
Recognition and modeling	Limitations imposed by dataset	15	[71, 77, 78, 84, 90, 91, 95, 105, 121, 122, 128, 145, 150, 156, 169]
Recognition and modeling	Accuracy limited by unimodal input	35	[47, 50, 53, 54, 57, 61, 86, 88, 104, 105, 110, 112, 120, 122, 125, 131, 132, 134, 135, 139, 140, 142, 143, 147, 149, 150, 152, 154–157, 167, 168, 173, 176]
Recognition and modeling	Accuracy limited by emotion model used	29	[42, 51, 74, 93, 101, 107, 109, 110, 114, 120, 121, 126, 127, 132, 138, 140–144, 146, 155, 157, 159, 163, 167, 170]
Recognition and modeling	Other	8	[41, 88, 90, 122, 131, 141, 144, 161]
Adaptation	Limited number of adaptation strategies	28	[10, 47, 50, 53, 54, 59, 60, 64, 71, 91, 93, 94, 98, 107, 115, 116, 120, 121, 128, 132, 136, 140, 142, 149, 153, 155, 162, 164]
Adaptation	Limited personalization due to lack of continuous learning from user	11	[74, 91, 103, 114, 129–131, 133, 141, 154, 169]
Adaptation	Need for real-time adaptation	6	[65, 72, 105, 117, 120, 140]
Adaptation	Dataset bias	5	[80, 92, 119, 138, 162]
Adaptation	LLM bias, unpredictability, or availability	4	[62, 68, 69, 86]
Adaptation	Limited language support from chatbots	3	[65, 125, 152]
General System Challenges	Limited user testing	18	[39, 50, 51, 57, 58, 94, 97, 108, 116, 118, 122, 129, 151, 155, 161, 165, 168, 170]
General System Challenges	Ethical and privacy concerns not properly addressed	19	[42, 53, 62, 69, 70, 73, 80, 98, 108, 112, 113, 125, 127, 132, 142, 143, 157, 160, 167]
General System Challenges	Scalability issues	3	[61, 139, 155]
General System Challenges	System was not implemented	7	[38, 41, 52, 87, 90, 113, 148]

Table 9: System challenges and limitations.

approval or compliance with GDPR, HIPAA, or similar guidelines. 65 (47%) conducted system testing, such as accuracy checks, benchmarking, or model comparisons.

Only 30 (22%) studies addressed ethical concerns, either as part of future work (see Table 9) or in some detail. Some addressed data privacy by anonymizing and deleting user data after use [98], or only processing it locally [139]. Some papers in the therapy and mental health domain stressed the importance of screening chatbot responses to avoid psychological harm [69, 98, 115].

4 Discussion & Limitations

This section first discusses the limitations this study faced, and then proceeds to provide an interpretation of the results.

Possible Impact of Feasibility Constraints

Due to time constraints, only systems from 2024 to May 2025 were included in the study, which severely limited the capacity to identify trends (SQ3b, SQ5b). Nonetheless, the survey still contributes valuable information about recent developments. Additionally, should more studies have been included, perhaps more systems modeling motivation would have been present. The six systems addressing motivation included in this study may not present a comprehensive overview of what models, adaptations and goals these systems have used so far.

Discussion of Results

As observed, the majority of systems are chatbots or recommendation systems. A potential reason for this could the fact that it is difficult to identify or classify intelligent systems. There are many systems which would fall under this category, however, very few papers which explicitly stated that they were adaptive or intelligent systems. On the one hand, this could be due to the fact only recently have researchers acquired the necessary computing resources to create these systems. As such, there is no consensus on a definition of what an intelligent system is, and only recently there have been developments trying to address this [13–15]. On the other hand, all systems fall under the category of affective computing, as defined by Picard in 1997 [177].

A considerable number of systems were tested, and it was determined that their accuracy is limited by the training dataset. Despite not always explicitly mentioned as a challenge, it could be argued that all systems which use FFA, SFA, NLP or other techniques which involve ML also share this limitation. It would be important for future authors of intelligent systems to address these concerns, and for more efforts to go into creating diverse, comprehensive datasets. On a similar note, there was a considerable number of systems whose emotion classification was unclear or done by ML, highlighting the need for explainable AI.

It was also noted that human emotions are complex and hard to identify, pointing to the need for more research into emotion recognition before these systems can actually be deployed. Similarly, but perhaps more importantly, the lack of a pattern in regards to motivation modeling outlines an even larger research gap to be pursued.

Finally, another important aspect of emotionally or motivationally aware intelligent systems are the ethical considerations. All systems involved in this study collect sensitive user data. As such, it is of paramount importance for these to address data privacy concerns, despite only 22% of papers even mentioning these limitations. Not properly addressing data privacy could lead to unethical data usage and abuse.

5 Responsible Research

This section discusses any ethical implications of the review in Subsection 5.1, measures taken to ensure the results are reproducible in Subsection 5.2, and the potential bias of the research in Subsection 5.3.

5.1 Ethical Implications

Conducting an SLR does not come with immediate ethical concerns regarding the research process, as all data used is publicly available. Even so, the results of this review could enable future unethical research. Despite not being the focus of this study, it is of paramount importance that future research is done into measures of enforcing data privacy and informed data usage consent, as well establishing regulations that safeguard users of future intelligent systems.

5.2 Reproducibility of Results & Large Language Model Usage

Reproducibility of results is an important aspect of any research study. By following standardized PRISMA reporting guidelines [34], all necessary information to repeat this study is present in the paper. All papers included in the study study are cited, and included in the bibliography. Additionally, all documents used throughout the research, such as all references included and filtered, document detailing the development of the search strategy, and full data extraction table have been uploaded to a public GitHub repository [5].

Furthermore, ChatGPT was only used in the research process to generate a script for counting the occurrences of each emotion, which is also available on GitHub and was manually checked by the author. ChatGPT was also used for shortening a few paragraphs in Section 3. A full list of the prompts and responses is presented in Appendix D.

[5]https://github.com/mirunic15/Research-Project-Documents

5.3 Risk of Bias

Risks are posed by the fact that the review was conducted by a single Computer Science bachelor student. Firstly, as this study addresses emotion and motivation, psychology background knowledge is necessary to fully grasp the situation. This addressed by an initial research phase into psychological theory of emotion and motivation. Even so, it was not possible to fully bridge this gap within the time frame of this project. Secondly, conducting an SLR in one person is bound to introduce mistakes and biases. To address this, the initial steps of developing the search strategy were carried out in a group of researchers conducting an SLR with the same research questions (but focusing on different cognitive-affective processes). This formed a common understanding of a conceptual model of an intelligent system. Furthermore, as mentioned previously, all steps of the process were documented and publicly uploaded to GitHub such that they can be retraced.

6 Conclusions and Future Work

In conclusion, this study conducted a Systematic Literature Review, surveying the usage of emotional or motivational data in the adaptation of intelligent systems. It explored input types and user models, and the types of adaptations systems perform based on these. It also looked at the challenges and limitations faced in the development of these systems.

The process involved the development of a rigorous search strategy and filtering steps, following PRISMA guidelines [34]. All steps were recorded and documented. A feasibility constraint was added, including only studies between 2024 and May 2025.

The review identified 139 relevant studies. From these, it was identified that the most prevalent emotion and motivation recognition techniques are facial and speech analysis, as well as natural language processing. In terms of emotions, categorical systems were widely preferred, constituting 81% of all systems. Despite the review aiming to look at motivationally aware systems, only 6 studies fit this category and showed no standardized modeling technique.

In terms of adaptations, the most identified systems were chatbots (33%) and recommendation systems (38%), primarily in the healthcare and entertainment domains. Common limitations researchers faced were limited recognition accuracy due to the lack of large, diverse datasets, and the use of a single type of input signal. Systems were also limited by the types of adaptations they could perform. Importantly, studies highlighted the need for more extensive user testing as well as the implementation of ethical measures to safeguard users.

In the future, the review should be expanded by removing the feasibility constraints. Researchers could build on the data from this study, excluding papers published after 2024, allowing for the identification of trends. Secondly, focusing on systems specifically targeting motivation could yield a better overview of modeling techniques used. Lastly, it would be interesting to explore the reasons behind popularity and acceptance of chatbots or music recommendation systems.

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A Aknowledgements

I would like to acknowledge my responsible professor and supervisor for providing support and constructive feedback all throughout this project. I would also like to thank all of my peers from the research group for their continued support.

B Full Queries

B.1 Full List of Synonyms

Key Concept	Synonyms
emotion	emotional state*, happy, sad, happiness, sadness, fear, anger, angry, disgust, surprise, stress, anxiety
motivation	motivational state*, extrinsic, intrinsic, user goal, goal-oriented, self-determination, self-efficacy, curiosity, aggression, fatigue, thirst, warmth, self-protection
user	person, player, student, teacher, learner, driver, pilot, patient
recognition	assess*, collect*, recogni*, detect*, identify, motivation-aware, emotion-aware, measure, classify, classification, emotional class*, motivational class*, profile, profiling, type
adaptation	adapt*, respon*, interactive, personaliz*, personalis*, react*, feedback
intelligent system	intelligent system, adaptive system, affective computing, human-robot interaction, chatbot, recommender system, adaptive user interface
review	survey, compar*

Table 10: List of key concepts and all synonyms used for query construction

B.2 Scopus

TITLE-ABS-KEY ((emotion OR motivation OR "emotional state" OR "motivational state" OR "happy" OR "sad" OR "happiness" OR "sadness" OR "fear" OR "anger" OR "angry" OR "disgust" OR "surprise" OR "stress" OR "anxiety" OR depress* OR "extrinsic" OR "intrinsic" OR "user goal" OR "goal-oriented" OR "self-determination" OR "self-efficacy" OR "aggression" OR "curiosity" OR "fatigue" OR "thirst" OR "warmth" OR "self-protection")

AND (user OR person OR player OR student OR teacher OR learner OR driver OR pilot OR patient)

AND (adapt* OR respon* OR interactive OR "personaliz*" OR "personalis*" OR react* OR feedback)

AND (assess* OR collect* OR recogni* OR detect* OR identify OR "motivation-aware" OR "emotion-aware" OR measure OR classify OR classification OR "emotional class*" OR "motivational class*" OR profile OR type OR profiling)

AND (intelligent system OR adaptive system OR affective computing OR human-robot interaction OR hri OR intelligent agent OR human-centered artificial intelligence OR hcai OR human-computer interaction OR chatbot OR chat bot OR robot companion OR recommendation system OR recommender system OR serious game OR intelligent user interface OR adaptive user interface OR learning system OR e-learning system OR learning environment OR e-learning environment OR aging-in-place environment OR social robot OR adaptive framework OR intelligent framework))

AND NOT (TITLE (review OR survey OR compar*))

B.3 Web Of Science

TS=(("emotion" OR "motivation" OR "emotional state*" OR "motivational state*" OR "happy" OR "sad" OR "happiness" OR "sadness" OR "fear" OR "anger" OR "angry" OR "disgust" OR "surprise" OR "stress" OR "anxiety" OR "depress*" OR "extrinsic" OR "intrinsic" OR "user goal*" OR "goal-oriented" OR "self-determination" OR "self-efficacy" OR "aggression" OR "curiosity" OR "fatigue" OR "thirst" OR "warmth" OR "self-protection")

AND (user OR "person" OR player OR student OR teacher OR learner OR driver OR pilot OR patient)

AND ("adapt*" OR "respon*" OR "interactive" OR "personaliz*" OR "personalis*" OR "react*" OR feedback)

AND (assess* OR collect* OR recogni* OR detect* OR identify OR "motivation-aware" OR "emotion-aware" OR measure OR "classify" OR "classification" OR "motivational class*" OR "emotional class*" OR "profile" OR "type" OR profiling)

AND ("intelligent system" OR "adaptive system" OR "affective computing" OR "human-robot interaction" OR "HRI" OR "intelligent agent" OR "human-centered artificial intelligence" OR "HCAI" OR "human-computer interaction" OR chatbot OR "chat bot" OR "robot companion" OR "recommendation system" OR "recommender system" OR "serious game*" OR "intelligent user interface" OR "adaptive user interface" OR "learning system" OR "e-learning system" OR "learning environment" OR "e-learning environment" OR "aging-in-place environment" OR "social robot" OR "adaptive framework" OR "intelligent framework"))

NOT TI=(survey OR review OR compar*)

B.4 IEEE Explore

(("All Metadata":"emotion" OR "All Metadata":"motivation" OR "All Metadata":"emotional state" OR "All Metadata":"emotional states" OR "All Metadata":"motivational state" OR "All Metadata":"motivational states" OR "All Metadata":"happy" OR "All Metadata":"sad" OR "All Metadata":"happiness" OR "All Metadata":"sadness" OR "All Metadata":"fear" OR "All Metadata":"anger" OR "All Metadata":"angry" OR "All Metadata":"disgust" OR "All Metadata":"surprise" OR "All Metadata":"stress" OR "All Metadata":"anxiety" OR "All Metadata":"depress*" OR "All Metadata":"extrinsic" OR "All Metadata":"intrinsic" OR "All Metadata":"user goal" OR "All Metadata":"goal-oriented" OR "All Metadata":"self-determination" OR "All Metadata":"self-efficacy" OR "All Metadata":"aggression" OR "All Metadata":"curiosity" OR "All Metadata":"fatigue" OR "All Metadata":"thirst" OR "All Metadata":"warmth" OR "All Metadata":"self-protection")

AND ("All Metadata":"user" OR "All Metadata":"person" OR "All Metadata":"player" OR "All Metadata":"student" OR "All Metadata":"teacher" OR "All Metadata":"learner" OR "All Metadata":"driver" OR "All Metadata":"pilot" OR "All Metadata":"patient")

AND ("All Metadata":"adapt*" OR "All Metadata":"respon*" OR "All Metadata":"interactive" OR "All Metadata":"personaliz*" OR "All Metadata":"personalis*" OR "All Metadata":"react" OR "All Metadata":"react" OR "All Metadata":"feedback")

AND ("All Metadata":"assess*" OR "All Metadata":"collect*" OR "All Metadata":"recogni*" OR "All Metadata":"detect*" OR "All Metadata":"identify" OR "All Metadata":"motivation-aware" OR "All Metadata":"emotion-aware" OR "All Metadata":"measure" OR "All Metadata":"classify" OR "All Metadata":"classification" OR "All Metadata":"profile" OR "All Metadata":"type" OR "All Metadata":"profiling")

AND ("All Metadata":"intelligent system" OR "All Metadata":"adaptive system" OR "All Metadata":"affective computing" OR "All Metadata":"human-robot interaction" OR "All Metadata":"HRI" OR "All Metadata":"intelligent agent" OR "All Metadata":"human-centered artificial intelligence" OR "All Metadata":"HCAI" OR "All Metadata":"human-computer interaction" OR "All Metadata":"chatbot" OR "All Metadata":"chat bot" OR "All Metadata":"robot companion" OR "All Metadata":"recommendation system" OR "All Metadata":"recommender system" OR "All Metadata":"serious game" OR "All Metadata":"intelligent user interface" OR "All Metadata":"adaptive user interface" OR "All Metadata":"learning system" OR "All Metadata":"e-learning system" OR "All Metadata":"learning environment" OR "All Metadata":"e-learning environment" OR "All Metadata":"aging-in-place environment" OR "All Metadata":"social robot" OR "All Metadata":"adaptive framework" OR "All Metadata":"intelligent framework"))

NOT ("Document Title":"survey" OR "Document Title":"review" OR "Document Title":"compar*")

C Full List of Identified System Objectives

List of identified objectives grouped by application domain. The numbers correspond to the indices in the table which can be found on GitHub (https://github.com/mirunic15/Research-Project-Documents):

- **Healthcare, Mental health, elderly care**
  - Make physical rehab more fun and engaging [10, 132]
  - Personalized adaptive resistance for exoskeleton? [117]
  - Combat lack of personnel or caregivers (Scalability) [10, 15, 35, 36, 61, 67, 76, 78, 82, 83, 90, 92, 93, 132, 136]
  - Provide constant support (Availability) [11, 15, 35, 64, 78, 82, 93, 94]
  - Help people get help without stigma (Stigma) [11, 15, 25, 31, 40, 67]
  - Help with costs [15, 67, 129, 136]
  - Simply making it more comfortable for people to get (Accessibility) [16, 31, 37, 40, 61, 64, 67, 90, 92, 95, 126, 129, 136, 139]
    - Specifically mental health for students
  - Mental wellbeing (Improve Mental)
    - Help with loneliness (Loneliness)
      - For elderly [4, 6, 30, 41, 104]
      - For students [125]
    - Encourage healthier lifestyle [6, 70, 133]
      - More physical activity for elders [6]
      - More physical activity in general [133]
    - Mood Regulation [8, 18, 37, 39, 48, 52, 76, 79, 84, 88, 95, 99, 105, 108, 112, 113, 114, 116, 122, 139]
      - Teach people how to do this on their own [37, 99]
    - Prevent more serious conditions (Prevention) [8, 37]
      - In students specifically [37]
    - Provide therapy-like or wellbeing suggestions and conversation (Suggestions Mental) [25, 37, 61, 65, 67, 83, 90, 92, 93, 94, 99, 126]
      - Specifically reminiscence therapy for memory issues like dementia [61]
      - Assist normal therapy methods, not replace [32, 36, 94]
    - New therapy method? Through music? [74, 79, 108]
    - Provide emotional support and companionship [32, 35, 42, 60, 64, 67, 82, 88, 126, 129]
      - Specifically for dementia [35]
      - Specifically for cancer patients [64]
    - Identify disorders (Identify Mental) [37, 85, 120, 125]
      - Identify emotional crisis situations and do something about it [11]
    - Simply more personalized care [15, 32, 95]
      - Specifically for students [95]
    - Promoting meditation [16]
  - Information overload problem in the context of personalized food recommendations (not healthcare) [58]
- **Education**
  - Improve online education [20, 75]
    - In light of COVID [20]
  - Improve student engagement and motivation, positive learning environment [20, 21, 45, 46, 75, 89, 115]
  - Make online learning more effective [23, 75]

- Personalized learning and assistance [34, 45, 46, 115]
  - Provide human-like tutoring [23]
- Reform online education with modern technologies [46]
- Deal with information overload [3]
- Provide real-time, 24/7 support [115, 135]

- **Marketing**
  - New marketing/business strategy [5]
  - Enhance customer satisfaction to enhance business profits [12, 28, 134]
    - Enhance brand connection [33]
    - Encourage buying [33]

- **Entertainment, Computer animation**
  - Keep streamer and chat engaged [17]
  - Just for funsies, Alan Turing [26]
  - Reduce cost of animation [27]
  - Improve connection between user and content
    - Music [44, 77, 121]
    - Multimedia [47]
  - Deal with information overload [1, 49, 50, 113]
  - Change way people find new content [1, 48, 71, 101, 102, 105, 110]
  - Gamification in non-game environment [7]
  - New game mechanics [14]
  - Simply more personalized experience [51, 52, 53, 55, 56, 59, 68, 69, 71, 72, 77, 106, 130]
  - Increase user retention [100]
  - Eliminate need for manual user reviews [103]

- **HCI, HRI, Smart Home, Driving, Productivity**
  - Better UX [38, 109, 120, 124, 128, 138]
    - More accurate recommendations [124, 138]
    - Empathetic, human-like responses [13, 62, 63, 65, 80, 91, 118]
    - Make interaction more human-like [43]
  - Improve accessibility of UI [54, 86, 87]
  - Enhance focus and productivity [86]
  - Assist humans in physical tasks (Physical HCI) [2]
  - Maximize user engagement [24]
  - Enhance bond with machine [24, 29, 81, 96]
    - Boost user engagement and bond with robot [19]
  - Make people more comfortable in their own house [57]
  - Make driving safer [96, 123]
    - Improve traffic flow [123]
  - Music that aligns with emotional state [111]

- **Future Uses**
  - Future uses [19]
  - More natural, human-like interaction [9, 98, 131]
  - More personalized experience [22, 51]
  - Prioritize novelty and serendipity in recommendations [97]
  - Engaging, emotional storytelling [127]
    * Make less lonely, emotional assistant, friend, foster creativity, help user with education
  - Check if distance from robot influences human interactions [137]
- **Other category**
  - Help families in stressful at-home situations due to fast-paced society [73]
  - Mental health: impact of empathy levels on interactions [85]
  - Unclear objective [107]

D List of LLM Prompts Used & Replies

Prompt 1: "i have this list of emotions per paper and i would like to show the percentage of each as a pie chart or something similar, can you please count the number of appearances of each emotion? please also mark unclear ones, and you can compress "happy" and "happiness" into the same category, you can do this for other emotions as well, but please do not group synonyms together (happy not the same as joy)"

Prompt 2: "can you rephrase this to be smaller, keeping as much of the original text and writing style as possible? please keep all of the citations in as they are"

Prompt 2.1: "In terms of visible inputs, the two most popular techniques are facial feature analysis and Natural Language Processing (NLP). The former refers to analyzing a user's facial expressions, typically from pictures or frames from a camera feed. The latter refers to various text-processing techniques. In most cases, a user simply inputs a text prompt which is later analyzed, however, systems sometimes perform speech-to-text conversion from a user's microphone feed.

Pitch, tone, intonation, volume, speed are all aspects of how a human speech that can indicate how a person is feeling. This has been classed as Speech Feature Analysis, and is done by analyzing audio clips and microphone input. Speech Feature Analysis is typically done in conjunction with NLP, as can be seen by the fact that only 3 [78, 153, 163] out of the 34 systems that do SFA do not also do NLP.

AAAA gaze tracking, head pose estimation [57], body posture and movement analysis [113, 140], hand gesture analysis [117], grip strength [129] and pressure analysis [106, 164].

Other techniques for visible inputs include mouse and keyboard activity [38], clicks and screen taps [87]. Systems also track user activity, such as what actions a player takes in a game [41], self-report questionnaires before and after an activity [103], how much a time a student spends on an exercise [108], or simply direct user feedback on whether they like the shown content [58, 90]. " **Response 2.1:** "The most common visible input techniques are facial feature analysis and Natural Language Processing (NLP). Facial analysis involves reading a userâs expressions from images or video frames, while NLP includes a range of text processing methods. Typically, users enter a text prompt, though some systems also use speech-to-text from microphone input.

Speech Feature Analysis (SFA) examines aspects of speechâpitch, tone, intonation, volume, speedâto infer emotions, using audio or mic input. SFA is usually paired with NLP, as only 3 [78, 153, 163] of 34 SFA systems omit NLP.

Other visible input methods include gaze tracking, head pose estimation [57], body posture and movement [113, 140], hand gestures [117], grip strength [129], and pressure sensing [106, 164].

Systems also use mouse/keyboard activity [38], clicks/taps [87], user behavior in games [41], pre/-post activity questionnaires [103], time spent on tasks [108], and direct feedback on content [58, 90]."

Prompt 2.2: "can you do the same for this Additionally, out of the 133 systems that adapt based on emotion, 87 systems use unimodal (U) input (only one type of input), and 46 (X%) use multimodal (M) input (more than one type of input, that is combined to determine the emotion). For motivation, 4 out of 6 use unimodal inputs, and 2 use multimodal inputs. Furthermore, systems can also be categorized based on whether the sensors they use are intrusive, disrupting the normal routine of the user, or non-intrusive. This is similar to the categorization in [NAME] [2], however, devices that a user would intentionally use everyday life such as a smartwatches or VR headsets were classed as non-intrusive, despite having to be worn. Intrusive systems include classic EEG machines which attach electrodes to a user's scalp, and chest-bands. These insights are visually quantified in Figure 3." **Response 2.2:** "Of the 133 emotion-adaptive systems, 87 use unimodal (U) input (a single input type), while 46 (X

Systems can also be classified by sensor intrusivenessâwhether they disrupt the userâs routine. Following [NAME] [2], devices like smartwatches or VR headsets are considered non-intrusive, despite being worn. Intrusive systems include EEG machines with scalp electrodes and chest bands.

These distinctions are illustrated in Figure 3."

Prompt 2.3: "All of the above mentioned categories aim to improve the way humans interact with technology. However, systems which did not mention a specific application domain or that they could be used in many application domains, the Human-Computer Interaction category was created. Human-Robot Interaction (HRI) was deemed a notable sub-domain as it refers to the interaction with computer systems on robotic platforms."

Response 2.3: "All the above categories aim to enhance human-technology interaction. Systems without a specific or with multiple application domains were grouped under Human-Computer Interaction. Human-Robot Interaction (HRI) was included as a notable sub-domain, referring to interactions with robotic platforms."

Prompt 2.4: "There is a wide variety of application domains, which are related to the goals of a system. This results in a wide variety of system objectives which would be too granular to present in a table. As such, they have been grouped by application domain, and an overview is presented in Figure 6. A detailed list of papers and the specific goals they aim to achieve is presented in Appendix [TODO]." **Response 2.4:** "System goals vary widely across application domains, making individual objectives too granular for tabular presentation. Instead, they are grouped by domain, with an overview in Figure 6. A detailed list of papers and their specific goals is provided in Appendix [TODO]."

Prompt 2.5: "In the healthcare domain, the most popular goals are helping users regulate their emotions, offering therapeutic guidance and advice, or simply provide emotional support and companionship. Other goals are related to making healthcare more widely available. Systems aimed to combat the need for more trained personnel (Scalability) and the need to have constant support (Availability), as well as encouraging people to get help, especially relating to mental health, by helping people avoid the stigma surrounding it (Stigma) and simply making it more comfortable (Ease of use). Notably, some papers mention that they aid to only support normal therapy methods and not replace these." **Response 2.5:** "In healthcare, common goals include helping users regulate emotions, offering therapeutic advice, and providing emotional support or companionship. Other aims focus on improving accessâaddressing the shortage of trained personnel (Scalability), ensuring constant support (Availability), reducing mental health stigma (Stigma), and improving comfort (Ease of use). Some papers emphasize that these systems are meant to support, not replace, traditional therapy."

Prompt 2.6: "When it comes to entertainment, the most notable goals are helping users navigate the large digital landscape, and help users in discovering content and feeling more connected to the content they interact with. Many simply mention the desire to offer a more personalized experience, without further elaboration. Some outliers are reducing the cost of animation, keeping the streamer and chat engaged, eliminating need for manual reviews and increasing user retention.

Educational systems typically aim to boost student engagement and motivation. A considerable number state wanting to make education more effective, but do not describe how this effectiveness is measured. An interesting objective is providing educational support around the clock. Many papers in this category also simply state the need for more personalized education.

Marketing systems aim to boost brand connection and customer satisfaction to enhance business profits. Interestingly, in the HCI domain the most prevalent goal stated is to simply improve user experience or provide more natural, human-like interaction, without further elaboration as to why this may be desired. Other interesting HCI objectives are making driving safer, assisting humans with physical tasks, or make UI more accessible for users with various impairments.

Outside of these categories, some systems did not mention a goal related to their application domain, but mentioned that they may have many potential future uses. For example, a recommendation system that can be trained on any dataset of items, and thus could be used for marketing, education, entertainment, etc. Standouts from the "Other" category are helping families in stressful at home situations, studying how empathy levels impact user-computer interactions, and a study which simply did not state any explicit goals [TODO]." **Response 2.6:** "In entertainment, key goals include helping users navigate digital content, discover new media, and feel more connected to what they consume. Many systems aim to offer a personalized experience, often without elaboration. Notable outliers include reducing animation costs, keeping streamers and chats engaged, removing manual reviews, and boosting user retention.

Educational systems commonly aim to increase student engagement and motivation. While many mention improving effectiveness, few define how it is measured. Some highlight goals like offering 24/7 support or enabling more personalized learning.

Marketing systems focus on strengthening brand connection and customer satisfaction to drive profit. In HCI, the most frequent goal is improving user experience or enabling more natural, human-like interaction, often without explaining why. Other notable HCI aims include safer driving, physical task assistance, and improving UI accessibility for users with impairments.

Some systems fall outside these domains, often suggesting broad or future use casesâe.g., a recommendation system trainable on any dataset. Standouts from the âOtherâ category include supporting families in stressful home environments, examining empathy in user-computer interaction, and one study with no stated goal [TODO]."

Prompt 3: "this section should become like half of its size To determine how the information regarding user emotion or motivation was used, the systems were classified according to their type. For instance, a system might achieve its objective of reducing a user's detected negative emotions, by providing emotionally intelligent responses. Another way it could achieve the same goal with the same information would be to suggest emotionally resonant music. Subsection **??** [TODO] discusses how the system types relate specific goals in more detail."

Prompt 3.1: "By far, the two main system types are Social Agents (SAs) (X% of all systems) and Recommendation Systems (RSs) (X% of all systems). SAs are systems that adapt various elements in order to facilitate conversations or social interactions, and are split into sub-categories. The first and largest, are chatbots. Chatbots adapt their responses, via text or text-to-speech, taking into account the content of the conversation and user state. The next category, Virtual Agents (VAs) go a step further and also adapt a virtual avatar's facial expressions, hand gestures and/or body posture. The "Other" category contains diverse systems. Some examples that stand out are: storytelling robots [58, 160] which adapt elements such as the speed, tone and type of story based on user state; a robot which performs dances to offer stress relief and companionship [72]; a dialogue mediator which facilitates conversation between a streamer and their chat [51]; a neuro-rehabilitation robot and virtual assistant combination, which adapts difficulty and offers human-like feedback [165].

In terms of RSs, they have been categorized based on the type of content they suggest. The recommendations are typically made via a dedicated platform, such as a web or mobile application, and adapt to a user's state. However, some [TODO] provide suggestions via a conversational interface. Some have not been categorized as chatbots as their primary purpose is to recommend content, and not engage in conversation. Others serve a dual purpose, and have received their own category. The "Other" category for RSs includes suggestions of gamification elements [41], food [91], physical activities [166, 176], art activities [167], or could be used to recommend anything [61].

Games represent computer programs which adapt elements such as difficulty, quests, character tone, and UI elements in a gaming context. The two driving systems stand out, one rhythmically inflates and deflates paw pads on a steering wheel to make the driver feel calmer, and maintain concentration on the road, as well as form a bond with their car [129]. The other switches control from the user to an autonomous driving system when a user is deemed in a depressed mood, to make driving safer [156]. Learning platforms adapt a multitude of elements, such as given assignments, gamification elements, tone of feedback. They usually perform more than one adaptation and act as a dedicated platform. Systems that simply suggest learning content without any additional features have been classed as RSs. The adaptive graphical elements category includes VR landscapes which change visual elements or background music [50, 149, 172], a desktop environment which changes color themes and wallpapers [119], or web platforms which change layouts and themes [87, 161], all based on user emotion.

Lastly, the "Other" category includes systems that generate content to fit a users preferences [80, 102], and an adaptive exoskeleton, which adapts the level of assistance it provides based on the valence of a user's emotion [150]."

Response 3.1: "To understand how systems use emotion or motivation data, they were classified by type. For example, a system might reduce negative emotions by offering empathetic replies or suggesting mood-matching music. A detailed mapping of system types to goals is in Subsection [TODO].

The two dominant system types are Social Agents (SAs) (X%) and Recommendation Systems (RSs) (X%). SAs facilitate conversation or social interaction and include chatbots, which adapt replies via text or speech, and Virtual Agents (VAs), which also adapt avatarsâ expressions and gestures. Notable examples in the âOtherâ SA category include storytelling robots [58, 160], dancing companions [72], a streamer-chat mediator [51], and a neuro-rehab robot assistant [165].

RSs adapt content suggestionsâlike music, videos, or articlesâbased on user state. Some use conversational interfaces, but are not chatbots if recommendation is their main function. âOtherâ RSs suggest gamification elements [41], food [91], activities [166, 176], or art [167].

Other system types include adaptive games (changing tone, difficulty, UI), and unique driving systemsâone inflating steering wheel pads to calm drivers [129], another switching to autonomous mode when users are depressed [156]. Learning platforms adjust assignments, feedback tone, and gamification elements; simple learning content suggesters are classified as RSs. Adaptive visual systems include VR environments [50, 149, 172], desktops [119], and web UIs [87, 161] that react to emotion.

Lastly, the âOtherâ category includes content generators [80, 102] and an adaptive exoskeleton that adjusts support based on emotional valence [150]."

Prompt 3.2: "Challenges and limitations were extracted based on what the authors stated, taking into account also what was classed as future work. The categorization is presented in Table 9. An observation is that 22 (X%) did not mention any limitations or challenges.

Many systems mentioned the need for more diverse or simply larger datasets for better user state recognition, and one [95] talked about the potential for biases to be introduced. Many systems simply mentioned the need for more diverse datasets to increase detection accuracy, however, some also stated that their systems struggled to detect rapid or subtle changes in user emotion [93, 94, 141, 163], or that specific emotions are underrepresented in their training dataset. Some other standouts also include systems which struggled with recognition in dark or noisy environments [90, 141, 144, 161], or a system that used facial emotions a game mechanic, which talked about the potential for a user to "fake" expressions in order to cheat the game [122].

For adaptation, many systems talked the need for more adaptation strategies. This includes the need for more songs or other recommendation options [107, 120, 128, 132, 140, 142, 153, 155, 164], the need for more response options for chatbots [10, 47, 54, 59, 64, 71, 94, 98, 115, 116, 121, 162], more robot movements [93] or animation options [53]. Interestingly, a considerable number of papers mentioned the lack of continuous learning from a user as a challenge. On the other hand, systems which did continuous adaptation, talked about having a cold start problem, namely lower system accuracy at the start, before enough user data is collected. Some papers also mentioned the need for real-time adaptations. From the "Other" category stands out a paper mentioning the need for the dataset of chatbot reposes to be continuously maintained in order to be kept up to date with the most recent psychological data [128].

The need for more user testing was also frequently discussed. This included the need to test in real-life conditions [**96**, 58], having a small sample size of users [57, 118, 122, 129, 155, 165, 170], and the need for long-term, longitudinal testing [108]." **Respomse 3.2:** "Challenges and limitations were identified based on author statements and future work, and are summarized in Table 9. Notably, 22 systems (X%) did not mention any.

A common issue was the need for more diverse or larger datasets to improve user state recognition, with one study highlighting the risk of bias [95]. Several systems struggled with detecting rapid or subtle emotional changes [93, 94, 141, 163] or suffered from underrepresented emotions in training data. Others noted limitations in dark or noisy environments [90, 141, 144, 161], and one game-based system mentioned that users could fake expressions to cheat [122].

In terms of adaptation, many systems cited the need for broader content options: more songs [107, 120, 128, 132, 140, 142, 153, 155, 164], chatbot responses [10, 47, 54, 59, 64, 71, 94, 98, 115, 116, 121, 162], robot movements [93], and animations [53]. Several papers noted the absence of continuous learning, while others that included it raised concerns about cold start issues-reduced accuracy early on. Real-time adaptation was also a common challenge. One paper stressed the need to continuously update chatbot datasets with current psychological data [128].

Many systems also emphasized the need for more user testing, including real-world conditions [**96**, 58], small sample sizes [57, 118, 122, 129, 155, 165, 170], and long-term studies [108]."

Prompt 3.3: "Out of all 139 systems, 29 (X%) did not mention any method with which they tested their system, out of which 5 were not implemented, justifying the lack of tests. 51 (X%) studies mentioned user testing or mentioned receiving some form of user feedback, out which only 13 mentioned receiving approval from an ethics committee or respecting GDPR, HIPAA or other guidelines. 65 (X%) studies did some form of testing on their systems, which primarily included accuracy testing against a datasets, benchmarking, but also comparisons with other similar models.

Secondly, only 30 studies mentioned ethical concerns of their system in some form, either as future work (see Table 9, or as having been addressed to some extent. For example, some systems talk about the need to address data privacy, and address it by anonymizing stored data and deleting it after use [98], or only processing the data locally on a user's machine [139]. Notably, some papers regarding chatbots in the therapy and mental health domain mention the need for careful psychological screening of responses, as these could have detrimental impacts on a users well-being [69, 98, 115]." **Respomse 3.3:** "Of the 139 systems, 29 (X%) did not mention any testing method; 5 of these were not implemented, explaining the omission. 51 (X%) reported user testing or feedback, but only 13 referenced ethics approval or compliance with GDPR, HIPAA, or similar guidelines. 65 (X%) conducted system testing, such as accuracy checks, benchmarking, or model comparisons.

Only 30 studies addressed ethical concerns, either as part of future work (see Table 9) or in some detail. Some addressed data privacy by anonymizing and deleting user data after use [98], or processing it locally [139]. Papers in the therapy and mental health domain stressed the importance of screening chatbot responses to avoid psychological harm [69, 98, 115]."