Past, Present, and Future: A Survey of The Evolution of Affective Robotics For Well-being

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***Abstract*—Recent research in affective robots has recognized their potential in supporting human well-being. Due to rapidly developing affective and artificial intelligence technologies, this field of research has undergone explosive expansion and advancement in recent years. In order to develop a deeper understanding of recent advancements, we present a systematic review of the past 10 years of research in affective robotics for wellbeing. In this review, we identify the domains of well-being that have been studied, the methods used to investigate affective robots for well-being, and how these have evolved over time. We also examine the evolution of the multifaceted research topic from three lenses: technical, design, and ethical. Finally, we discuss future opportunities for research based on the gaps we have identified in our review – proposing pathways to take affective robotics from the past and present to the future. The results of our review are of interest to human-robot interaction and affective computing researchers, as well as clinicians and well-being professionals who may wish to examine and incorporate affective robotics in their practices.**

***Index Terms*—affective robotics, survey, well-being, affective computing, human-robot interaction**

I. Introduction

According to the World Health Organization (WHO), well-being is defined as "a positive state experienced by individuals and societies" and "is a resource for daily life and is determined by social, economic and environmental conditions [1]". Yet, approximately 1 in every 8 people, or 970 million individuals worldwide, were living with a mental disorder in 2022, and mental, neurological, and substance use disorders account for 10% of the global burden of disease and 25.1% of non-fatal disease burden [2]–[4], and more than 80% of people with mental health conditions lack access to quality and affordable care [5]. This has created a pressing need to support people's well-being.

Affective Robotics offers a promising approach to enhance human-robot interaction and improve overall well-being by studying how robots can recognize, interpret, process, and simulate human affect [6]. Since the beginning of research in social robotics [7] in the early 2000's, the ability to understand human affect and emotion has played a key role in enabling robots to be helpful in various application areas [8]–[10], especially for mental health and well-being support [10]–[12]. For example, affective robotics have been used to lead mindfulness meditations [13], facilitate social bonding [12], support diet and physical activity [10]. In these contexts, being able to recognize and generate affect is extremely important because the goal of the interaction involved tracking or supporting a "positive state" in the user.

However, studying, developing, and designing affective robots for well-being is still an open research area due to multiple challenges in this research landscape. First, affective robotics is an interdisciplinary research topic that combines the fields of Affective Computing and Human-Robot Interaction. This intersectionality brings together multiple disciplines, making it challenging to consider various aspects simultaneously (**Challenge 1**, C1). To address this complexity, the field of affective robotics must tackle several challenges. It should develop computational models that accurately understand, model, and adapt to human behaviors. These models must be embedded into robotic platforms that can be used in real-world applications, such as well-being (*technical* challenge). Affective robots must be designed with features that enable smooth and seamless interaction with humans. This includes understanding how to design the robots themselves and how they can effectively interact with humans (*design* challenge). Affective robotics has a responsibility to develop fair and ethical computational models, particularly in high-stake application scenarios like well-being. Additionally, the field must conduct studies that are ethically compliant and ensure the well-being of both humans and robots involved in these interactions (*ethics* challenge).

Second, affective robotics relies on advancements in affective computing, which utilizes cutting-edge artificial intelligence (AI) models to understand human emotional states. However, the field of AI has undergone *rapid evolution*, particularly in recent years, with an unprecedented growth in AI advancements (**Challenge 2**, C2).

Third, research on affective robots for well-being has primarily focused on a few sub-areas, such as dementia, with limited studies in other cognitive impairments like schizophrenia, depression, ADHD, and intellectual disability. Recent efforts involve collaborating with domain experts, such as mental health professionals and well-being experts, and including stakeholders in the design and research processes. However, it remains unclear how affective robotics can support patients and extend clinical care systems across diverse well-being domains and how much these stakeholders are involved in the research process and how interdisciplinary collaborations are conducted (**Challenge 3**, C3).

Therefore, we conducted a literature review of the last 10 years of research in affective robotics for well-being from different point of views, namely technical, design and ethical,

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to better understand the multi-facet complexity of this research field (addressing C1, **Solution 1**). This review focused on the trajectory of the affective robots for well-being. Specifically, we identified existing gaps and areas that need further investigation, and provided insights into future opportunities to improve the state of the art and close the gaps (addressing C2, **Solution 2**). In this review, we have also identified: i) domains of well-being that have been studied in affective robotics research and establish which areas are still unexplored and warrant further exploration, ii) the current methods used to investigate affective robotics for well-being, and iii) how these research processes and methodologies have changed over time (addressing C3, **Solution 3**).

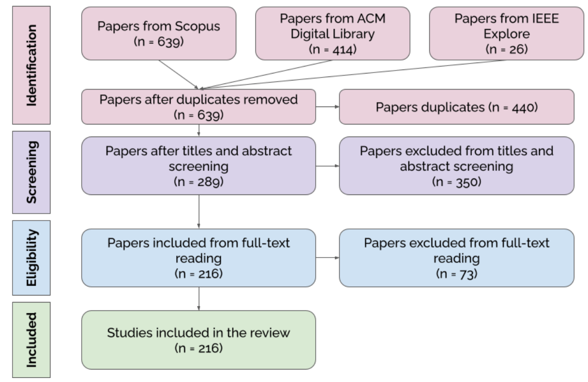

Fig. 1. PRIMA Schema for our systematic review.

II. Background and Definitions

The field of Affective Robotics (AR) has been increasingly applied in various domains, such as healthcare and well-being applications, where affective robots have demonstrated significant potential [14]. With the term well-being, we refer to a comprehensive concept that encompasses what it means to be functioning as a healthy person across multiple domains [15]. For example, mental well-being is about achieving a positive state of mind [16] and it involves aspects like the ability to cope with challenges, recognizing personal strengths, and finding purpose in daily life.

Affective Robotics is at the intersection between Affective Computing (AC) and Human-Robot Interaction (HRI) fields. AC is an emerging interdisciplinary field that integrates the affective and computational sciences and studies how machines can measure human affective states [17]. Analogously, HRI is also an interdisciplinary field that encompasses expertise from cognitive, psychology, robotics, design and computer sciences, and it aims at understanding the dynamics in human-robot interactions [18]. As a result, Affective Robotics inherited the interdisciplinary nature of both AC and HRI fields when applied in a well-being context. From a computational and **technical** point of view [6], affective robotics research needs to: (i) understand human behaviours while interacting with robots; (ii) model human-inspired behaviours in robots; (iii) adapt to the interaction context to meet the personal needs of humans interacting with the robot; and (iv) translate the results obtained in controlled settings into real-world scenarios without compromising performance and efficiency. From a **design** point of view (i.e., how to design robot features and interactions with humans), the affective robotics field lags behind the advances in the HRI field in which researchers collaborate with domain experts, e.g., teachers, psychologists, to design robots that can be used in real-world scenarios [13]. The involvement of stakeholders is not an easy task, but it becomes fundamental when applying technologies such as robots to high stake contexts like well-being. From an **ethical** perspective (i.e., considering moral, value and legal implications), the potential for both positive and negative outcomes in well-being context makes it an ethically complex issue, requiring careful ethical consideration to achieve a balance between the positive and negative aspects [19]. The AC community has made efforts in this direction by including a mandatory Ethical Statement section in the International Conference on Affective Computing & Intelligent Interaction (ACII) submissions, and by investigating the current ethical issues, positive and negative, which arise from the current state of affective computing [19]. However, these efforts have not yet been translated into the area of affective robotics.

Previous efforts have been made to survey the current state of the art of affective robotics field, e.g., [6], [20]–[22]. For example, [6] reviewed the last decade of affective robotic works in well-being focusing only on technical aspects without including any considerations for ethics or design. [20] conducted a literature review on affective touch during human-agent and human-robot interactions. [21] reviewed the past works on robotics for mental health and well-being without focusing on affective aspects, similarly to [22] which focused exclusively on the introduction of robots in health psychology applications (e.g., behavioural change and emotion regulation interventions). None of these previous surveys have provided a comprehensive snapshot of the last decade in affective robotics for well-being and a future research agenda for the field focussing on the multi-disciplinary aspects that characterise it, namely technical, design and ethical.

Therefore, in this paper, we conducted a survey to review the papers from the last decade on affective robotics for well-being by analysing the evolution in this research field from technical, design and ethical point of views.

III. Method

This section describes the methodology to identify the papers included in this survey by reporting the procedure, the search query, the inclusion criteria, the selection process, the data analysis and extraction, and the terminology used.

A. Procedure

To define our systematic literature review approach, we followed the guidelines established by Nightingale [23] and we expanded upon a previous preliminary survey on this topic undertaken by two authors of this work [6]. Our methodology adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [24], widely acknowledged as the gold standard for systematic reviews and meta-analyses. PRISMA ensures the quality and replicability of the review, organizes the final manuscript using standardized headings, and facilitates the assessment of the study's strengths and weaknesses [23]. Specifically, the PRISMA framework presents an evidence-based, minimal set of reporting items for systematic reviews, structured around a four-phase flow depicted in Figure 1. The initial phase involves identification, wherein all potential manuscripts are gathered. Subsequently, during the screening phase, papers meeting the eligibility criteria are selected based on an assessment of their titles and abstracts. In the selection phase, full texts are scrutinized, and only those meeting the same eligibility criteria are retained. Finally, in the inclusion phase, all selected papers undergo analysis to address the study's research questions.

B. Search Query

We gathered papers based on the terms found in their titles, abstracts, and keywords, utilizing the Scopus, ACM Digital Library, and IEEE Xplore databases. Scopus was selected due to its broad coverage across multiple disciplines beyond computer science. The ACM Digital Library and IEEE Xplore were chosen for their extensive coverage in human-computer interaction, computer science, and engineering. The search queries were adjusted slightly to accommodate the requirements of each database. We provide the search query used for Scopus:

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TITLE-ABS-KEY ( ( "affective robotic*"
OR "social robot*" OR
"emotional robot*" OR "socially
assistive robot*" ) AND (
"wellbeing" OR "well-being" OR
"mental health" OR "health" ) )
AND PUBYEAR > 2012 AND
PUBYEAR < 2023
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We executed the search queries to identify potential papers for review. After that, we removed duplicate entries and stored references in a Google Sheet file.

C. Eligibility Criteria

Papers were included only if:

- they address well-being or health (both physical and mental)
- they model, analyse, design, or discuss the ethics of affective capabilities of a robot
- use/discuss physical robots (e.g., video-conference, video)
- their title, abstract, and keywords contain at least one keyword describing such technology and one keyword from the Search Query Keywords.
- the robot is acting as an agent not as a tool (medium, e.g., to connect people)

Papers were excluded if:

- they were published before May 2012 and after the day of actual running of the search query, i.e., Oct 31, 2022,
- they are not in English,
- they are not in peer-reviewed journals and conference proceedings,
- they are surveys, (not provide any additional contributions, e.g., tools or protocol),
- they are inaccessible to the authors,
- they are low quality (i.e., they do not report the details necessary to evaluate their eligibility)

D. Selection Process

All manuscripts collected from the databases were screened based on their titles and abstracts. Then, a thorough examination of the full texts was conducted to ensure compliance with the eligibility criteria.

Prior to the screening process, a random sample of 5 papers was selected from the 2022 Scopus search and evaluated by five reviewers to establish consensus on inclusion and exclusion criteria. All reviewers had a full agreement on the inclusion or exclusion of the sample papers. The remaining papers were then randomly distributed among the reviewers, with each reviewer screening a subset individually. Screening of titles and abstracts was conducted according to the predefined eligibility criteria. In cases where a reviewer had uncertainty regarding a particular paper, it was flagged for further discussion among all reviewers. The same set of reviewers were subsequently assigned different subsets of manuscripts for full-text screening and data extraction.

In total, 639 papers were collected using the specified search query (refer to Figure 1). These manuscripts underwent initial screening based on titles and abstracts, resulting in the selection of 289 papers. Their full texts were reviewed. This process yielded a final count of 216 manuscripts, as reported in the Supplementary Materials. Among these 216 manuscripts, a total of 239 studies were identified, with some papers containing multiple studies.

The comprehensive list of extracted papers is publicly accessible via a spreadsheet stored in the GitHub repository[1].

E. Data Analysis and Extraction

We defined a set of variables that can help understand the evolution of this field – encompassing various types such as numerical (e.g., number of participants in each study), categorical (e.g., type of the robot), or qualitative (e.g., design methods) – by creating a codebook of variables that can be found in the same Github repository. We extracted relevant information from each paper using an analytical approach to assign a value to each of the defined variables. For numerical variables, we employed a descriptive statistics description, while qualitative variables were analyzed using pattern-based methods. Categorical variables were derived through either a top-down or bottom-up approach as in a previous work [25]. The former involved pre-defining variable categories based on existing literature. The latter approach entailed extrapolating variables from the collected data among the selected papers. These variables are collected in Table I.

F. Terms

The following paragraphs describe the terminology used in this survey.

[1] https://github.com/Cambridge-AFAR/aff-rob-survey.git

TABLE I
LIST OF VARIABLES EXTRACTED FOR EACH PAPER, THE CORRESPONDING TYPE AND EXAMPLE OF VALUES.

Variable	Type	Example
Year	numerical	2013, 2014, etc.
Authors' discipline	categorical	computer science, psychology, etc.
Country	categorical	USA, Finland, Japan, etc.
Study type	categorical	qualitative, quantitative, etc.
Psychological target outcome	categorical	anxiety, depression, etc.
Application scenario	categorical	education, therapy, play, etc.
Experimental setting	categorical	school, lab, workplace, etc.
Number of sessions	categorical	single, less than 30, more than 30
Number of participants	numerical	10, 22, etc
Study design	categorical	single-session, within-subject, etc.
Target population	categorical	neurotypical, elderly, dementia, etc.
Age range	numerical	7-10 years-old
Mean age	numerical	9.4, 75.3 etc
Gender	categorical	female, non-binary, male, others
Robot model	categorical	NAO, Pepper, Mario, etc
Mode of interaction	categorical	physical, virtual, video, picture
Robot operation	categorical	autonomous, wizard of Oz, semi-autonomous
Affective behaviour generation	qualitative	facial expressions, expressive movements, etc.
Generation autonomy	categorical	autonomous, wizard of Oz, semi-autonomous
Affective behaviour perception	qualitative	human facial expressions, human movements, etc.
Perception autonomy	categorical	autonomous, wizard of Oz, semi-autonomous
Technological aim	categorical	Yes, No
Design aim	categorical	Yes, No
Ethical aim	categorical	Yes, No
Inclusion of clinicians	categorical	Yes, No
Theory-grounded	categorical	Yes, No
Data collection method	categorical	questionnaires, survey etc.
Computational models	categorical	statistics, ML, deep learning etc.
Design approach	qualitative	participatory design, user-centered, etc.
Stakeholder involvement	categorical	young adults, clinicians, etc.
Ethics on user safety	qualitative	deception, human contact, etc.
Ethics on societal impacts	qualitative	fairness, justice, bias, etc.
Ethical implications	categorical	Yes, No
Ethics approval (internal)	categorical	Yes, No
Ethics approval (external)	categorical	Yes, No

a) Author disciplines: We defined the authors' disciplines taking the categories defined by [18]. As a result, we identified the following 15 categories of disciplines: art, biology, business, communication, computer science, dentistry, design, education, engineering, humanities, literature, medicine, philosophy, psychology, and social sciences.

b) Study type: With this term, we refer to the type of study that was conducted by authors, specifically we categorised the studies into qualitative, quantitative, theoretical, and meta-analysis works.

c) Study session: With this term, we refer to the number of sessions in which participants of each study interacted with the affective robot.

d) Psychological target outcome: The psychological target outcome is the specific psychological construct that the robots target or treat [26],for example, anxiety, loneliness, depression, or well-being. Notably, some studies of affective robots focus on well-being, whereas others target specific mental health outcomes (e.g., depression; anxiety). Mental health is typically more narrowly defined as the absence of certain disorder-specific symptoms. Wellbeing represents a broader term that may encompass factors such as overall ability life satisfaction, ability to cope with stress, and resilience.

e) Application context: This refers to the specific conditions and settings in which study and/or findings are intended to be applied, and we identified the following categories: educational (e.g, the robot teaches, population's learning), therapeutic (that includes both assessment and treatments or interventions [25]), mental (i.e., improves psychological well-being, like stress, anxiety, can be corollary to main diagnosis), health (i.e., any paper which focuses on public health and general well-being contexts, and does not fit into either of the others), psychological (i.e., specific psychological phenomena, e.g., joint attention, theory of mind), home (i.e., robots intended to be used either at home or residential centers), creative (i.e., improve people creativity), play (i.e., robots that promote play and game activities), social (i.e., the development of a social relationship with the robot), others (i.e., if no context is specified). The definitions of such application contexts are in line with previous work by [18].

f) Experimental setting: The experimental setting is the environment where participants interacted with the robot, for example laboratories, schools, homes, etc.

g) Study design: This is the design of the study that can be within-subjects, between-subjects, random control trails, among others [27].

h) Mode of interaction: This variable refers to the modality of the interaction between the robot and the human. For example, if participants were asked to evaluate a robot just watching a video of the robot we labelled it as "video" mode of interaction, while if the participants interacted physically with a robot that have been categorised as "physical".

i) Robot operation: The robot operation refers to how the robot was controlled, and we identified the following categories: wizard-of-oz (if the robot was controlled by the researchers or participants in the study), semi-autonomous (following the definition in [18], e.g., if the robot performed actions autonomously but the decision are controlled by the researchers), and autonomous (if the robot could perform autonomously the whole interaction).

j) Affective behaviour generation and perception: With these variables, we want to label studies according to the capabilities of the robot to generate or express affect-based behaviours (e.g., facial expressions), and the capabilities of the robot to perceive affect-based behaviours following the suggestions in [6].

k) Aims: Motivated by the multi-disciplinary nature of the affective robotics field and the challenges that emerged in the literature (see Section II), we defined three specific aims for the studies surveyed: technical (i.e., studies that examine AR from a technological perspective, for example works that presented a computational model to automatically detect emotions in human-robot interaction), design (i.e., studies that examine AR from a design perspective, for examples works that presented a focus group to design features of an affective robot), and ethical (i.e., studies that examine AR from an ethical perspective, for example works that have investigated the ethical implications of introducing robots in public spaces).

l) Theory grounded: This variable refers to the studies that used and implemented systems, artifacts, or features backing it up with psychological theories (e.g., theory of mind).

m) Data collection method: This variable refers to the methodology adopted for collecting data in studies, for example questionnaires, interviews, and surveys.

n) Computational models: This variable refers to the type of computational models used in the studies to develop the affective system/artifact/features.

o) Design approach and stakeholder involvement: These variables include which design methods have been used to design AR, the interaction, or parts of the robot and whether stakeholders were involved or not in the design process of such AR. For eample, we categorized surveyed papers by the following criteria: 1) if the paper claimed to apply participatory or co-design, we assigned it to that label, 2) if the paper claimed neither participatory or co-design, but described the involvement of users, we assigned it a user-centred design label, 3) if the paper claimed neither of those, we assigned it as Not Reported.

p) Ethics on user safety, society, and implications: These variables encompass whether the paper discussed implications of user safety (e.g., deception, human contact) or societal impacts (e.g., fairness, bias, and justice). Moreover, notes were collected on the specific aspects and categories of ethical discussion that were later organised and classified based on the framework in [28].

q) Ethics approval: With this variable, we labelled all the studies that have received an approval from internal (e.g., university) and/or external (e.g., hospital) entities.

IV. Evolution of Affective Robots for Well-being

This systematic review aims to better understand the evolution of affective robots for well-being in the last decade, from technological, design, and ethical perspectives to tackles the challenges C1 and C2 reported in Section I. This section describes the evolution of technological, design, and ethical aspects in the context of affective robotics.

A. Technical and Computational Advancements Over Time

We found 21 studies that have only a technical contribution (i.e., their main contribution was focusing only on technical aims) among 81 studies that also focused on technical aspects alongside design and ethical aims. This aligns with the inherently multidisciplinary nature of the HRI field, as highlighted by [29]. Technical aspects were the focus of the field since the raise of HRI [30]. Consequently, HRI in recent years incorporates insights from various disciplines, including ethics and design, in addition to technical contributions.

We classified technical studies based on the computational models employed, perception and generation capabilities of the affective robot explored, and the robotic platform used for such applications.

1) Computational Models: In terms of computational models employed in affective robots, interestingly, until 2017, studies employed affective robots using variety of computational techniques (e.g., control systems, algorithms, state machines and cognitive architectures) as shown in Figure 2. However, between 2017 and 2019, studies started employing statistical models via empirical research, with almost all of the research conducted being empirical. Generally, statistical models have been the most popular computational models used in affective robotics studies (46% of the studies). This is followed by studies deploying AI-based models on affective robots (27%) (such as deep learning models, machine learning, reinforcement learning, and natural language processing), which gained popularity in 2020 (more than 50% of the studies), 2021 (40% of the studies) and 2022 (50% of the studies). The increasing use of AI-based models over statistical methods signifies a desire within the field to develop more sophisticated models aspiring for automation. These models aim to accurately learn from large datasets to recognize, interpret, and respond to human affective states, thus adapting to the state-of-the-art in affective computing and machine learning at large.

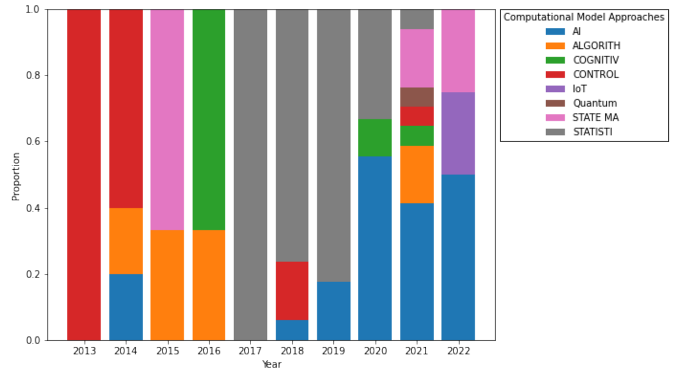

Fig. 2. Proportion of computational model approaches per year. "AI" stands for the application of AI models like machine learning, deep learning, and reinforcement learning, "ALGORITH" stands for algorithmic based operation system, "COGNITIV" stands for computational models aimed at following cognitive principles, "CONTROL" stands for human control systems, "IoT" stands for Internet of Things - systems that facilitates communication between devices and the cloud, "Quantum" stands for computational models that are based on quantum computing, "STATE MA" stands for State Machine - a behavior model that consists of a finite number of states, "STATISTI" stands for the application of statistical model for empirical evaluation of affective robotic interactions.

2) Affective Capabilities: The affective perception capabilities embedded in robots evolved from a single modality emotion recognition model, where the majority of the studies used facial expression recognition systems until 2020, to a multi-modal emotion recognition approach in which authors have begun to explore data-driven approaches from multiple data sources (e.g., in [31], the authors considered facial expressions and touch behaviour to detect emotions). While autonomous affective perception in studies primarily relied on the robot's ability to perceive emotions from facial expressions without human intervention, a different pattern emerged for affective generation capabilities of robots that utilized both WoZ (Wizard of Oz) and autonomous data-driven computational models. This is due to the need of controling the interaction to ensure most of the effects come from the generated behaviour of the robot, and recently this trend is evolving by using more autonomous generation. This shift is due to the current advancement in AI in general, and generative AI in particular [32] that exploded in the last few years. However, the generation of human-like behaviours (e.g., facial, speech, gestures) is still a challenge that needs further investigation within affective computing [33].

Most studies on behavior generation in human-robot interaction have focused on linking generation to a specific interaction paradigm, rather than solely investigating computational affect generation models. For example, [34] designed a robot that could generate empathic behaviors in order to optimize user engagement. This approach prioritizes creating interactions that foster empathy, as opposed to solely exploring computational models of affect generation. The development and implementation of computational models to generate affective behaviours may be very challenging and it may also have limitations in capturing the nuances and contextual factors involved in human emotional expression and perception. Therefore, grounding affect generation in specific interaction paradigms like human-robot interaction in well-being applications may yield more insightful results for better understanding the complex nature of affective behaviours.

3) Robotic Platforms: Lastly, we identified humanoid robots as the most common robotic platforms (52%) within the technical studies. They are followed by machine-like (17%), pet-like (11%), and bio-inspired (2%) robots. The remaining studies did not report the robotic platform used. Over the past decade, humanoid robotic platforms like Nao and Pepper have remained relatively unchanged, while the adoption of computational models has increased significantly. This raises concerns about the appropriateness of these platforms for AI-based interactions, given their limitations in terms of computational capabilities and adaptability. These platforms, indeed, present to date several limitations, making it more challenging to deploy such robots in everyday lives and for daily applications. First, the current robotic platforms lack sufficient local computational power, which is crucial for processing complex AI models and handling large amounts of data in real-time [35]. To date, researchers use largely cloud computing or external service APIs that lead to latency and reduced responsiveness, making interactions less seamless and less natural [36]. Second, the computational models and algorithms used in these robotic platforms are often not designed to handle the complexity and variability of real-world interactions and to be embedded into a robot. This can result in robots that are not able to effectively learn from their interactions with humans or adapt to contextual situations. Last, the robotic platforms are often designed for specific tasks (e.g., QT robot for interacting with children with autism [37]) or applications, which limits their scalability and flexibility. This makes it difficult to re-use them for different tasks in real-world scenarios.

B. Design Research Changes Over Time

76 of the surveyed works were classified as having a design focus. In general, our data shows that the most design-focused works in affective robotics were published in 2018 (13 works) and 2019 (14 works), increasing steadily from 2013 (1 work) to this point, and then decreasing from 2020 (9 works) onward (see Fig. 5). As pointed out by Lupetti et al. [38], the first explicit design track was introduced in the HRI conference in 2015 [39], and Ro-Man conference in 2016 [40]. The increasing number of design works in our data aligns with the established design tracks in 2015 and 2016, placing an emphasis on design work published in the following years.

In our data analysis, we classified each paper to have either affective aims (i.e., the study had an explicit aim of exploring the affective design, capability, etc. of a robot) or an affective component (i.e., the paper explores affective robots, but does not have it as its main focus). Out of 76 design works, 24 had affective aims. The peak of the proportion of design studies with affective aims was in 2017 (57%), where it rose to steadily from 25% in 2015, and fell steadily to 11% in 2020 (see Fig. 3). A recent peak in affective aims was in 2020 with 50%. However, no design works with affective aims were observed in 2022. These trends may indicate a cyclical interest in exploring affective aims in design studies, with no clear increasing or decreasing trend.

1) Level of User Involvement: We classified the 76 identified design studies into categories based on the level of user involvement: 14 participatory design (or co-design), 57 user-centred, and 5 none reported.

From 2018 onward, the proportion of reported participatory design contributions has been increasing (8% in 2018, reaching 38% in 2021 and 33% in 2022, see Fig. 4). According to Bodker, the second wave of HCI which initiated around 1999 and continuing until 2006, placed an emphasis on user-centred design and participatory design [41]. As the design tracks at the HRI and Ro-Man conferences were only established in 2018 and 2019, the HRI design trends may be following HCI, with a delayed increase in participatory design when compared to HCI. Indeed, Lupetti et al. [38] identify an increasing trend toward user-centred design and including users in the design process through participatory methods in HRI [38]. This aligns with the work of Alves-Oliveira et al. [42], calling for more user-involved design to truly address user needs and problems.

However, published design works in affective robots for well-being have decreased from 2019 (14 works) to 2022 (6 works). This decrease may be related to the challenges in designing social robots, e.g., design for purpose and artificial emotion expression [42]. Designing affective robots for well-being specifically has several unique challenges, such as appropriately personalizing verbal expressions while preserving well-being practice [13], and incorporating stakeholders such as carers into the robot design [43]. Additional challenges emerge when researchers attempt to design affective robots intended to be deployed in healthcare systems for direct patient care. Designs must consider how an affective robot could fit into an already-complex clinical workflow, how to ensure appropriate patient privacy and risk management (e.g., in the case of suicidal thoughts expressed), or how to prioritize stakeholder engagement with a multidisciplinary treatment team. Such factors may make the (co-)design of affective robots for well-being more challenging.

2) Who Are Involved in Design Studies: In the PD studies, 6 out of the 14 studies reported children or teenagers as co-designers. The WHO has recommended early detection and intervention as one of the key strategies in improving young people's mental health and resilience [44]. Using PD strategies with this group in particular may reflect one of the key aims of PD: empowering the users of the designed technology [45]. Three of the PD studies described involving mental health professionals (e.g. psychologists or mental health coaches),

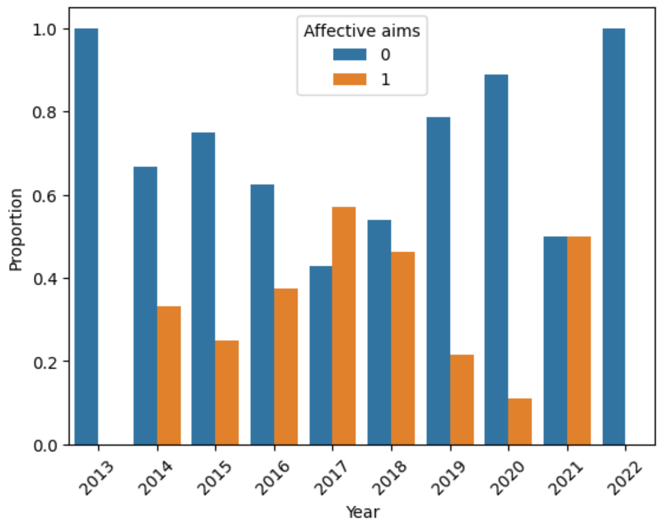

Fig. 3. Proportion of affective aims in design studies (1) and affect-related studies (0) by year.

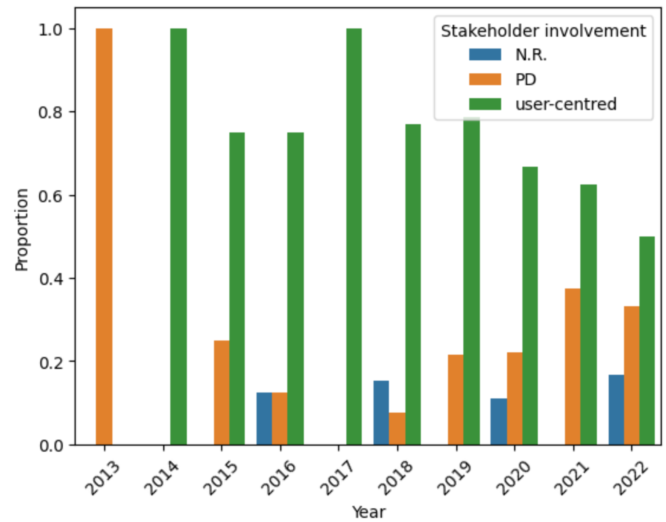

Fig. 4. Stakeholder involvement proportions in design studies by year.

and two mentioned involving familial caregivers.

In the 57 user-centred studies, 22 involved clinicians (e.g., healthcare staff or disability service workers), and 5 of them involved family members or informal caregivers in the design process (four of these studies focused on older adults and their unique challenges (e.g., dementia), and one for children's kinesiology. 29 of the studies explicitly collaborated with (prospective) end-users. These figures reflect that most of the studies focused on collaborating with only one of the stakeholder groups (i.e. end-users or other stakeholders). Only 9 of the studies focused on multiple stakeholder groups (e.g., both patients and clinicians). The tendency to focus on a single stakeholder group is understandable from a pragmatic perspective but may limit external validity given the highly multidisciplinary nature of applied patient care. Given that many affective robots are intended to be deployed in healthcare settings, an important future direction for user-centered design studies will be to involve patients, caregivers, and a range of different provider types, ideally together as part of a collaborative design process.

3) Ethics in Design Research: The number of design studies that discuss ethical implications has been generally increasing, climbing from 29% in 2017 to 83% in 2022 (see Fig. 6). In recent years, works have called for the integration of ethics into the design process [13], as well as striving toward equitable robot design [46]. These works emphasize the importance of diverse user and stakeholder involvement [46], [47]. Overall in our dataset (from 2013-2022), a higher percentage of design studies with *vulnerable* user groups (e.g., neurodivergent children, people with PTSD or other mental health issues) discussed ethical implications (43%), compared to studies with non-vulnerable user groups (31%). This is not surprising and encouraging as it is often suggested that vulnerable populations can be disproportionately impacted by unethical design choices [48].

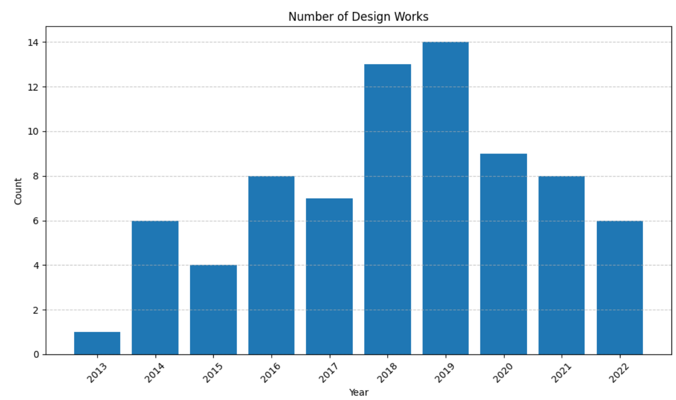

Fig. 5. Number of design works by year.

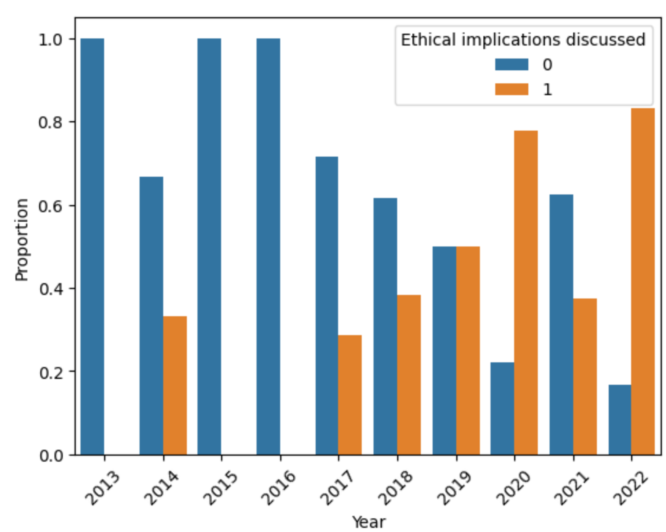

Fig. 6. Proportion of design works that discussed ethical implications by year.

C. Ethical Considerations and Guidelines

Overall, very few papers were written with a dedicated critique of the ethical concerns related to their work, e.g. discussing safety, fairness, privacy etc. of their application. Only 36 papers were identified as having a primarily *ethical* theme (i.e., the primary contribution is a discussion of the ethics of robots for well-being), and only 41% of papers had any mention of ethical implications. As such it is difficult to complete a quantitative assessment of ethical implications. We will instead perform a more qualitative assessment, classifying discussions and discussing trends.

1) Discussions of Ethical Implications: For each of the papers that was flagged to have discussed ethics in some form a freehand note was provided with the keywords and main topics of concern brought forth in the paper. Multiple frameworks exist to guide ethical discussions of affective systems including [48], [49] however, these systems have a primarily AI focus. We had only 40% of our papers using autonomous capabilities [49] with 14% having affect generation, less than 1% having affect perception [48], and 16% having both affect generation and perception capabilities. However, as part of our inclusion criteria, all papers were required to include a social robot. As such, to guide the conversation on ethical implications we will refer to “A Code of Ethics for the Human-Robot Interaction Profession” [28]. Here the authors suggest four primary categories of design principles to consider for human interaction: Human dignity considerations, Design considerations, Legal considerations, and Social considerations. Each of the noted discussion topics were organized into one of these 4 categories with one additional category “societal considerations” that includes topics pertaining to infrastructure, employment and similar topics. In Fig. 7 we see that dignity and design implications are most often discussed. Examples of dignity considerations that were seen include emotional needs, such as: autonomy, person-hood, and preference; rights to privacy, such as: monitoring, data privacy and policing; and respect for humans’ emotional and physical frailty, such as: negative reactions, emotional exploitation, embarrassment, infantilization, powerlessness, infection, and physical safety. For design consideration, we saw commentary on topics such as, trust, reliability, equity, fairness, ableism, control, transparency, accessibility and maleficence. Legal considerations included topics such as informed consent, liability and accountability, and social considerations included attachment, deception and coercion.

Although we see a vast array of ethical topics discussed, we note that instead of many papers each commenting on a few ethical considerations impacting their study, we instead saw papers (69) that had more thorough discussions of several ethical implications. Regarding the sub consideration provided by Riek and Howard [28], all of the Human Dignity considerations are considered in ethical discussions of our sample, however, the other three considerations are missing several applicable discussion points. We instead see the authors opting to consistently refer to the same topics presented in the previous paragraph. For design considerations there is a lack of consideration of opt-outs and kill switches, real-time status indicators and predictability of behaviour. Legal considerations, in general, are not thoroughly discussed. Yet, with the advent of the new EU Artificial Intelligence Act [50] these discussions will become exceedingly important. For social considerations, two important considerations were lacking: reducing the use of WoZ to avoid Turing deceptions [51], [52] and limiting humanoid morphology. Both of these techniques are regularly employed in social robotics for well-being with 40% of papers using WoZ techniques and 52% using humanoid robots. However, we do not see an increase in the discussion of social considerations in WoZ studies (Fig. 8). Roboticists will often employ WoZ to pilot ideas and reduce the burden of programming as well as the possibly of mistakes, however, these techniques involve deceit and can be particularly difficult for vulnerable uses and may result in increased expectations for robot behaviour that contradicts the considerations of predictability in design.

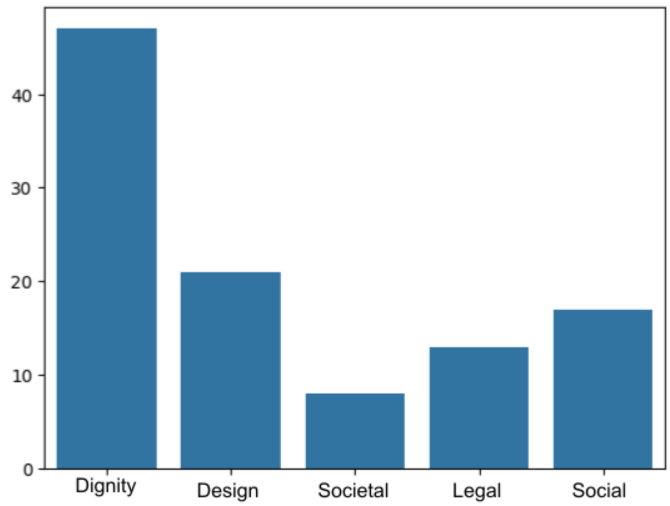

Fig. 7. Counts of ethics categories.

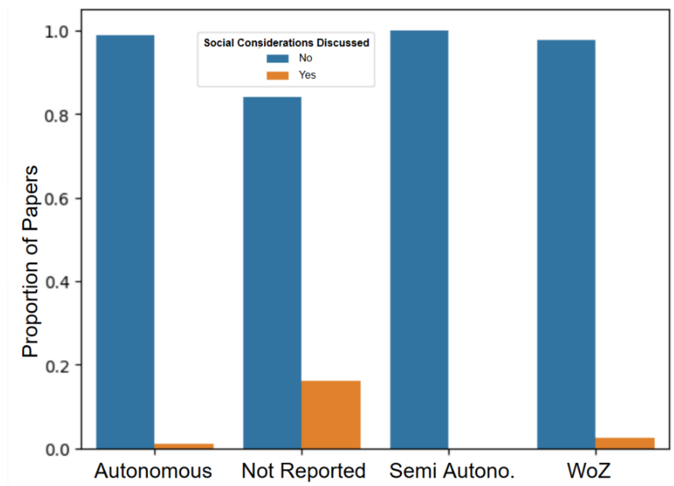

Fig. 8. Proportion of papers with social discussion topics by robot operation.

2) Disclosure of Ethics Approval: With the recent focus on Equity, Diversity and Inclusion (EDI), the number of institutions and granting agencies requiring a disclosure of ethics approval appears to be increasing. External approval shows no trends, with only 10 total papers (5%) disclosing external approval. However, we do see the expected trend in internal ethics approval disclosure. Overall 101 (47%) of the papers disclosed internal approval, yet, as can be seen in Fig. 9 (left), previous to 2017 the proportion ethics approval disclosures was quite low. Although there has been an increase, we are still only seeing disclosure of ethics approvals in about half of the papers. These results tell us that most institutions are handling ethics themselves. Although it appears only half of the research institutions are requiring a disclosure of ethics approval, it is, nevertheless, difficult to comment on the amount of institutions requiring ethics approval for these studies as this amount is likely higher than that of the disclosures as researchers themselves may have chosen not to disclose the approval. Geographically, we see that Eastern, Western, and Southern Europe, as well as Western Asia stand out as having a lower ethics disclosure proportions, Fig. 9 (right). These discrepancies may be a result of funding and institutional regulations where the institution or funder requires the disclosure of ethics approval, or possibly cultural norms [53].

3) Application Scenarios and Populations: Observing the proportions, interestingly, the highest proportion of papers containing ethical discussion are in applications within the home (Fig. 10), followed by those employed to increase children's creativity, education, and health. Most of these scenarios likely include interaction with children, which may play a role in the need to carefully consider ethical implications. Interestingly, psychological use cases have a lower proportion of ethics discussions, despite the sensitive nature of these applications. To delve further into this research question, we explored whether research where the target population was primarily vulnerable (e.g., neurodivergent children, people with PTSD or other mental health issues) more often discussed ethical considerations [54]. Vulnerable target populations included, but were not limited to those involving children, the elderly and people with intellectual and physical disabilities. Yet, we do not see a noticeable difference in the proportion of papers discussing ethics for vulnerable populations (Fig. 11).

Unlike with the disclosure of ethics approval we do not see a trend in the discussion of ethical implications over time, Fig. 12. The sole outlier here is the most recent year, 2022, where the number of papers discussing ethical implications was equal to those that did not. However, it is not possible to speculate if this was unique to this year of publication, or whether it will continue to the future.

V. 10 Years of Affective Robotics

This section reports the most relevant results on research methodology, topic, aims, outcomes, and robotic operations collected from our systematic review by analysing the last decade in affective robotics for well-being, addressing **C3**.

Note that a comprehensive report of the results can be found in the Supplementary Material, and that this section is only meant to give the reader an overview of affective robotics for well-being field to better understand the evolution of the technological, design, and ethical aspects of the field in the last decade, as described in Section IV.

A. Research Methodology

Our observations indicate high variability in the research methodology of affective robotics studies, marked by variations in data collection methods, participant recruitment, and the duration of studies.

1) Data Collection methods and type of studies: We observed interesting trends in data collection methods and their evolution over the years as shown in Figures 13. Quantitative studies have predominantly shaped the field of affective robotics, accounting for 39% of the studies published and showcasing a methodological preference for measurable, data-driven insights. Although quantitative studies predominate the field, qualitative and mixed-methods studies are also prevalent. Qualitative studies account for 28.9% of the studies, and mixed-methods account for 13.4% of the studies. Over time, we have observed a notable increase in the number of qualitative and mixed-methods studies, indicating a gradual shift towards a more holistic understanding of affective interactions with social robots. Specifically, there was a marked increase in qualitative studies in 2022 (75% of the studies). This could be due to restrictions on conducting behavioural experiments during the COVID-19 pandemic, leading many researchers to work with smaller samples and rely on qualitative methods. This evolving blend of methodologies highlights a dynamic, multifaceted research landscape that adapts to the complex nature of affective interactions in robotics.

Another point of interest is the low proportion of system studies (4% of the total number of studies), with most studies published between 2013 (13% of the studies) and 2015 (17%). It is presumed that during this period, the field of affective robotics was in a more developmental stage, focusing on building and assessing foundational systems crucial for establishing baselines and understanding the capabilities of these affective agents. Post-2015, the focus might have shifted towards refining these systems based on initial findings and integrating them into more complex user studies to explore the broader implications of affective robotics in various contexts and settings. This shift could be an indicator of technological maturity, where incremental improvements and applications of existing systems became more relevant for advancing the field. For example, as affect detection models were advancing in the broader affective computing community, affective robotics researchers gradually applied these advancements empirically to their own systems rather than developing dedicated systems from scratch [55]. Another possibility is that system-related research in affective robotics is now broader, encompassing disciplines like social robotics, affective computing, machine learning, natural language processing, and computer vision [56], [57], with these systems then applied in affective robotics research.

2) Number of Participants: We observed growth in the average number of participants per study over the years, indicating a trend towards larger sample sizes to enhance the robustness of findings as shown in Figure 14. This increase,

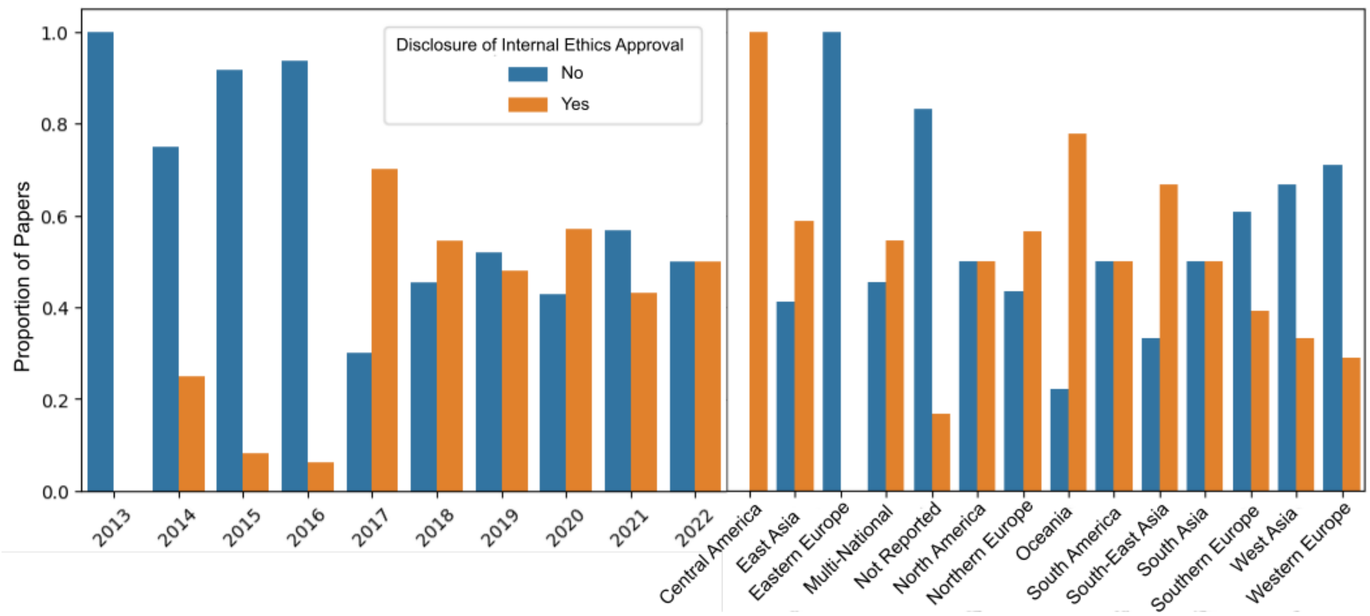

Fig. 9. Proportion of papers providing internal ethics disclosure, left: by year, right: by geographic region

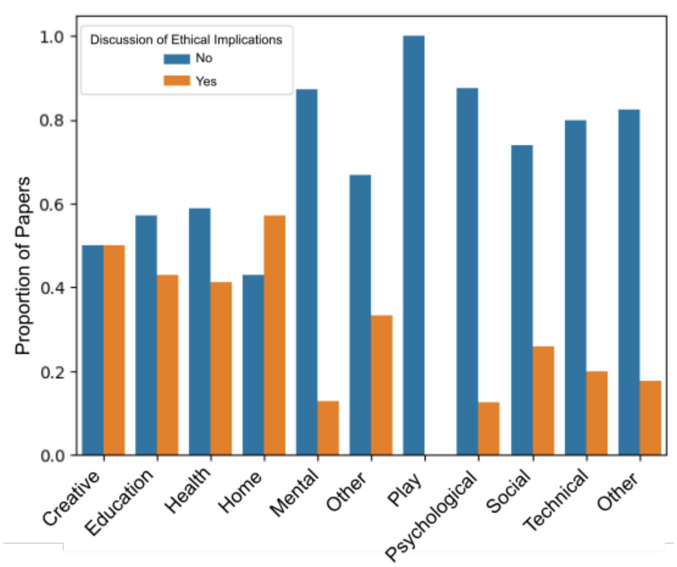

Fig. 10. Proportion of papers discussing ethical implications by application scenario.

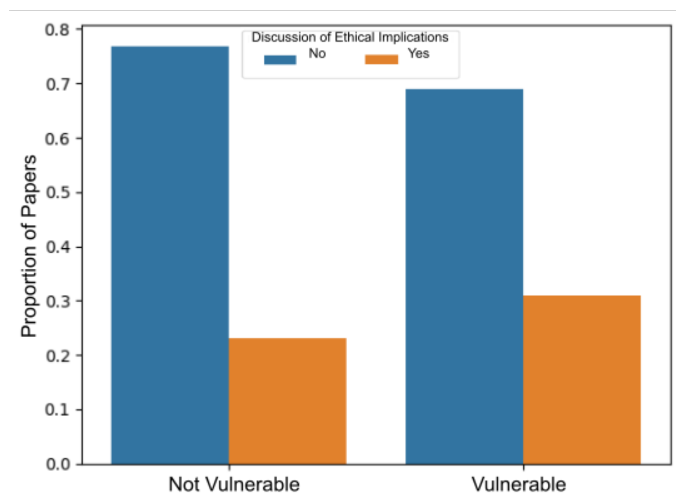

Fig. 11. Proportion of papers discussing ethical implications for vulnerable populations.

from approximately 30 participants per study on average in 2013 to almost 100 participants per study on average by 2022, underscores efforts to ensure findings are robust and widely applicable, essential for technologies that closely interact with human emotions and behaviours. It should be noted that some of these studies are neither empirical nor quantitative in nature, and thus the extent of their contribution and methodological rigour is not assessed by the size of their sample.

3) Study Sessions: We found that single-session studies have emerged as the predominant focus in affective robotics (72% of the total number of studies), with a notable peak in long-term studies (lasting up to 10 sessions) published in 2021 (39% of the studies), as depicted in Figure 15. However, the overall trend for long-term studies is characterized by sporadic spikes rather than a consistent increase or decrease. This preference for single-session studies may be attributed to researchers prioritizing the assessment of technological developments and the introduction of new affective features. Such studies allow for rapid validation of innovations, keeping pace with the swift technological advancements in the field [6]. This approach underscores a dynamic and evolving research ecosystem, where the drive for innovation often outweighs the desire for long-term deployment insights. The fast-paced nature of technological progress in affective robotics may also explain this preference for single-session studies: long-term studies could be perceived by researchers as less relevant, as technology could become outdated by the time a study concludes [58]. Additionally, logistical and financial con-

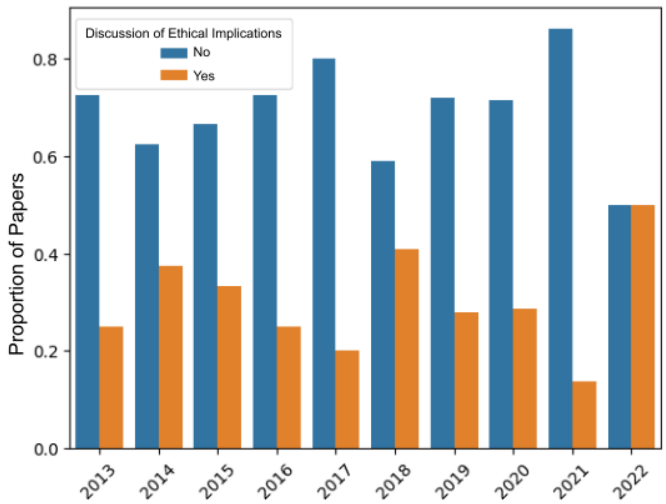

Fig. 12. Proportion of papers discussing ethical implications by year.

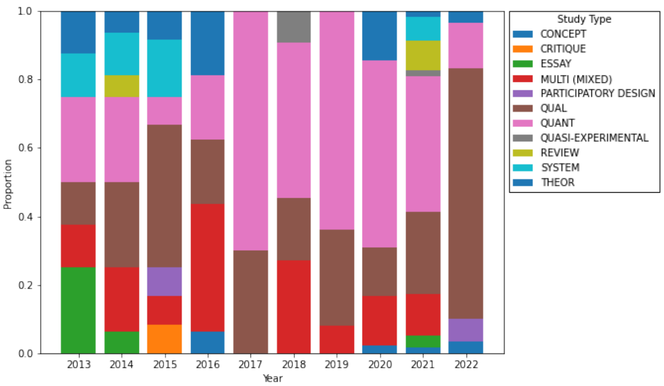

Fig. 13. Proportion of study types per each year.

straints, along with the challenges of maintaining participant engagement over extended periods, may discourage longer study durations [59], [60].

B. Aims and Applications

Affective robotics is a relatively wide area of research, encompassing studies with various aims, disciplinary affiliations,

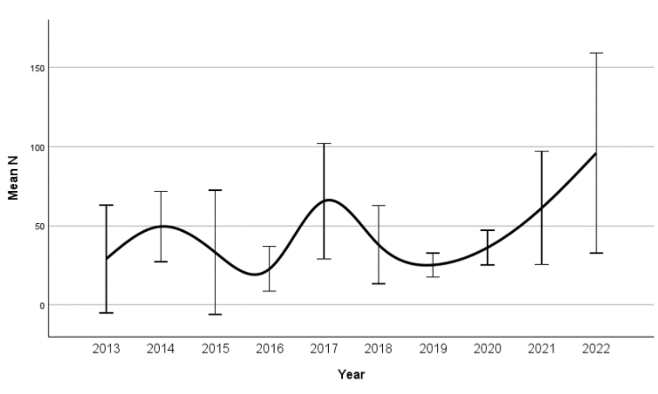

Fig. 14. Average number of participants in a study per year

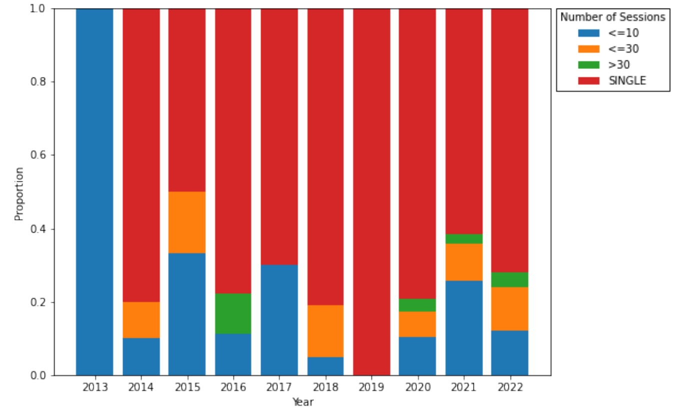

Fig. 15. Proportion of studies with employing different number of sessions per each year.

and application scenarios.

1) Aims: Three main aims were identified in the literature published between 2013 and 2022: technological, ethical, and design, as shown in Figure 16. Regarding technological aims, we observed a steady positive trend in the proportion of studies including technological aims over the years, reaching a peak of over 60% of studies published with technological aims in 2021. In terms of ethical aims, our data show that studies published rarely include these aims, with a maximum of slightly more than 20% of the studies including ethical aims (in 2014, 2019, and 2022). Regarding design aims, most studies published in affective robotics tend to include such aims, ranging between 70% to 95% of the studies published per year, with the exception of 45% in 2021.

Our results show that only three papers (1%) cover all three aspects, namely technological, design and ethical, while 14% focused on technical and design, 2% on technical and ethical, and the 11% on ethical and design aspects. The majority of them (72%) focused on only one aspect. The limited integration of technological, design, and ethical aspects in research could potentially be attributed to the complexities and resource constraints of addressing multiple aims simultaneously, which is a common challenge in human-centred engineering and computer science research [61], [62]. Specialization in one aspect is often required by the need for depth and clarity in research, especially in early stages, alongside academic and publication pressures that prioritize quicker, focused studies. As the field evolves, interdisciplinary collaborations may facilitate more holistic approaches with varying aims.

2) Discipline Affiliations: The research diversity in affective robotics is also evidenced in the presence of single and multidisciplinary teams, and disciplinary affiliations. Over the years we can observe that there are more studies published by single-discipline teams over multidisciplinary teams, with the exception of 2018 with 61.9% of the studies published being by multidisciplinary teams. Nonetheless, in most years we can observe that between 27% (in 2019) to 44% (in 2015 and 2017) of the studies published in each year were by multidisciplinary teams (with the exception of 6% of the studies in 2016, and 61.9% of the studies in 2018). This seems

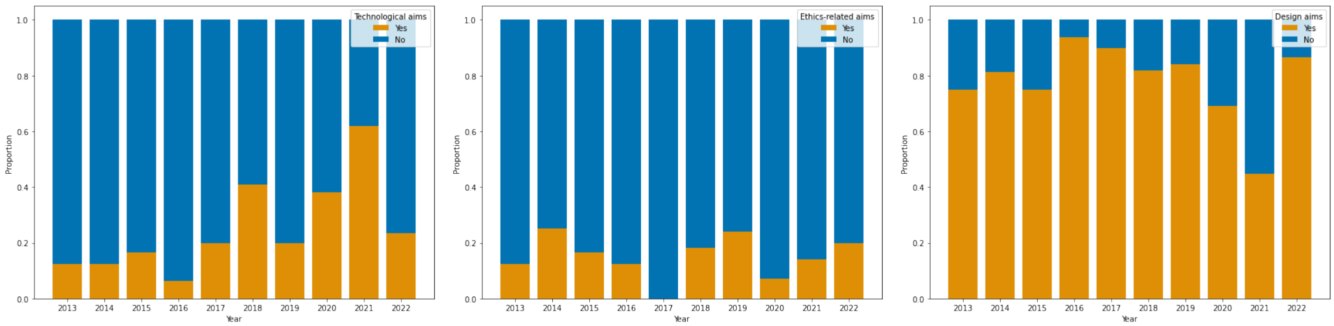

Fig. 16. From top left to right: (1) proportion of studies including technological aims per year. (2) proportion of studies including ethical aims per year. (3) proportion of studies including design aims per year.

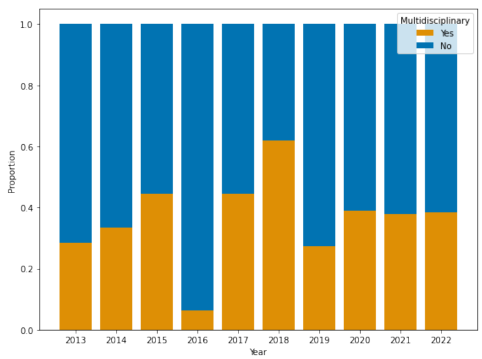

Fig. 17. Proportion of studies with multidisciplinary and single discipline teams per each year.

like a relatively high ratio of multidisciplinary efforts.

Single discipline studies have seen a surge of papers from authors with a computer science background, followed by papers with authors with an engineering background, and then a media background. Surprisingly, single discipline studies coming from psychology see only a maximum of 30% of the papers in a year (in 2018). Given that '*Affect*' at its core is a psychological construct [63], and given the broader connection of the field to '*Psychological Well-being*' [22], it is expected that researchers with a background in psychology would be more prominently involved, similar to related fields such as social robotics and HRI [64]. Studies published by multidisciplinary teams sees similar trends, with most of the first authors in these teams having computer science background. Accordingly, we can assume that despite the multidisciplinary nature and demands of affective robotics research, the field is still primarily driven by technical questions and aims.

3) Application Contexts: We observed that a substantial proportion of the studies published in affective robotics are concerned with health application scenarios (28% of all studies) ranging between 20% (in 2019) to 58% (in 2015) of the studies published in a year (except for 10% in 2017). This is followed by studies concerned with social application scenarios (21% of all studies), ranging between 6% (in 2016) and 31% (in 2014) of the studies published in a year (except for 0% in 2013). This is an important trend in affective robotics, stressing that despite the technical aim that dominates the field (with explicit research aims and disciplinary affiliations), many of the studies are aimed at being applied in typical social contexts that are customary in affective computing (i.e., health and social settings). Following these two application scenarios (i.e., health and social settings), the third most prominent application scenario is mental health, constituting 16.3% of the papers. Hence, while socially assistive robots have been studied in a variety of health-related settings, including physical rehabilitation and primary care [22], research into affective robotics considers role of social robots in mental health settings and other applied care scenarios to be critical within the field.

This approach is also evidenced by the growing proportion of studies focused on well-being target outcomes, increasing from 17% in 2014 to 36% in 2022, with a peak of 55% of all psychological target outcomes in affective robotics research observed in 2020. However, it is important to consider the generality and breadth of the field. This is evidenced from the proportion of studies with multiple outcomes, ranging from 65% of the psychological target outcomes of affective robotics papers in 2013, to 80% of the affective robotics papers published in 2016. As noted previously, there has been a shift towards more studies investigating well-being outcomes—a term that is in itself vague and broad. Nonetheless, starting in 2017, we began to observe a diversification of outcomes studied, with many (15 identified) unique psychological target outcomes related to well-being identified, such as eating disorders, eldercare, sleeping habits, stress-related issues, and psychopathologies, among others. This diversification suggests that beyond the growing interest in the health and well-being applications of affective robots, the field is maturing. Researchers are increasingly seeking to assess the applicability of this technology for addressing specific outcomes (e.g., behavioural changes related to eating and sleep, or emotional support for loneliness and stress), rather than attempting to capture multiple outcomes in single studies [22].

VI. Future Opportunities in Affective Robotics for Well-being

Our survey aims at better understanding the evolution of affective robotics for well-being over the last decade. Our results show the past and present of this research field, and this section explores the future opportunities in affective robotics

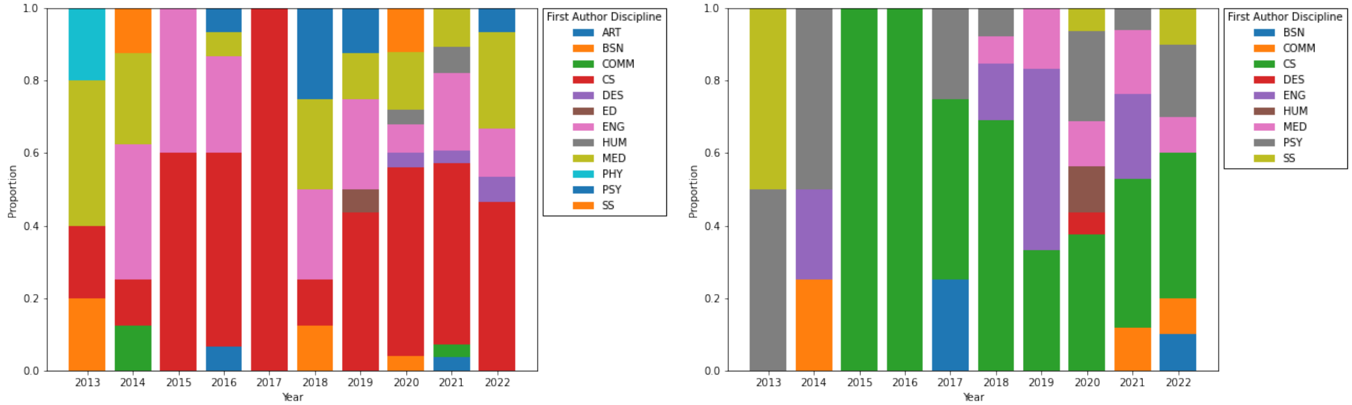

Fig. 18. From left to right: (1) Proportion of first author disciplinary affiliation within studies with single discipline teams per each year. (2) Proportion of first author disciplinary affiliation within studies with multidisciplinary teams per each year.

TABLE II
PAST, PRESENT AND FUTURE OF AFFECTIVE ROBOTICS ACROSS TECHNICAL, DESIGN, AND ETHICAL ASPECTS.

Aim	**Past**	**Present**	**Future**
Technological (Models)	Models embedded in robots were mainly about control systems	Models are characterised by machine learning and AI-based methods	Research should investigate foundation models for both perception and generation
Technological (Robot)	Humanoid robotic platforms have been developed with pre-programmed functioning	Humanoid robotic plaforms are the same, and external computational	New robotic platforms that should enable AI-based models to run locally
Design (Affective Interest)	Increasing interest in designing robots with affective purposes	Lack of interest in designing robot for affective purposes	Design works should focus on the human-centered affective capabilities
Design (User Involvement)	Few works have conducted PD studies	PD method has been conducted with single stakeholder groups	Co-design, like PD, works should include multiple groups of stakeholders
Ethical (Inclusion)	Very few works included information about ethical approval or implications	About half of studies include ethical approval and even fewer include ethical discussion	Beyond ethical approval, works should include discussions on implications using guidelines like the code of ethics and considering the EU AI Act

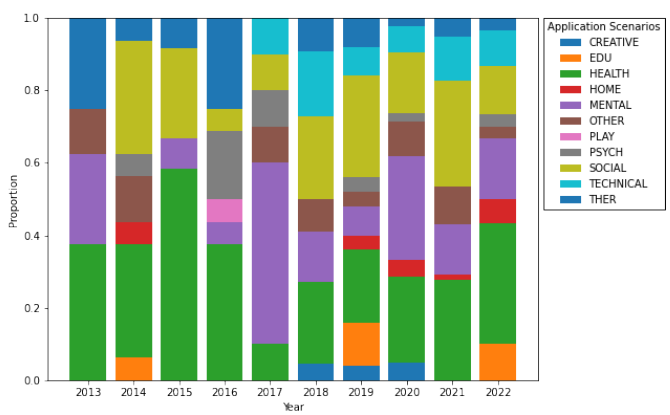

Fig. 19. Proportion of studies employed in different application scenarios per each year.

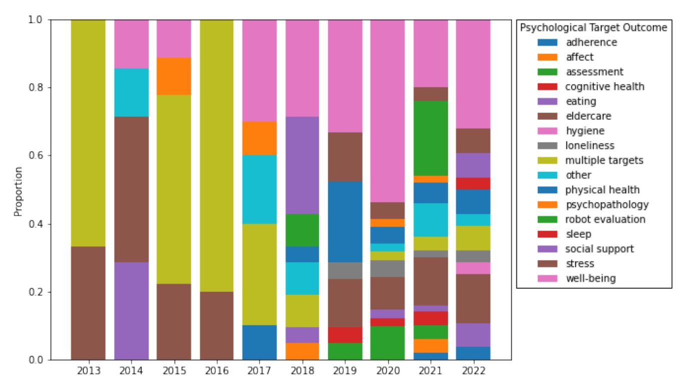

Fig. 20. Proportion of studies employed for studying different psychological target outcomes per each year.

distilled for well-being across technical, design and ethical aspects as collected in Table II.

Affective robotics is a multi-disciplinary field that includes expertise from computer scientists, psychologists, social scientists and roboticists. As such, this field would benefit from the cross-fertilization of affective computing and robotics [65]. We observed that in the earlier stages of affective computing research, there was more emphasis on empirical, data-driven studies to establish the foundational understanding of affective phenomena [6]. More recently, we note a shift in the research landscape, potentially driven by the very recent technical advancement in the field. This shift in the research approach, from more empirical to potentially more technical, could indicate that the field of affective computing research is maturing and transitioning towards more sophisticated, application-oriented developments.

This **technological** shift in affective robotics for well-being can manifest in different forms, such as advancements in affective sensing and generation techniques, integration of affective AI models into robotic platforms, exploration of real-world applications of these technologies in well-being contexts, and increased interdisciplinary collaboration between technical and social/behavioral researchers. As we have already mentioned, the field of affective robotics is increasingly shifting towards data-driven models, and we will observe an even more evident shift in the future driven in part by the emergence of large language models (LLMs) that are revolutionising various domains. This trend is not limited to affective robotics but is part of a broader movement encompassing human-computer interaction (HCI) [66], computational linguistics [67], and affective computing [68]. It is essential to go beyond solely utilising LLM APIs and consider how these models can be tailored to specific use cases, focusing on quality-centric data rather than quantity, especially for high-stake domains like well-being. Improving relationships with the affective computing community and enhancing the benchmarking of models intended for implementation in interactions are crucial steps for advancing the affective robotics field. Therefore, we encourage researchers to collaborate, leverage current advancements, and explore their practical application in real-life social interactions like well-being with robots.

Future investigations in affective robotics for well-being are likely to focus on the technical challenges and opportunities associated with integrating multimodal affective data into LLMs for robotic applications [69], [70]. This could involve exploring novel architectures, training methodologies, and evaluation metrics tailored to the unique requirements of multimodal language understanding in well-being contexts. We hope that future researchers can build a new generation of intelligent and emotional robotic systems that can seamlessly process and respond to various sensory inputs, paving the way for enhanced human-robot interaction in well-being.

From a **design** point of view, co-design of affective robots for well-being is underexplored, and is a future research opportunity. Especially in clinical contexts, designing with multiple stakeholders (i.e. clinicians, other healthcare workers, and patients) in the same room could be useful for establishing a dialogue between them, and empowering patients in how future robotic technologies could contribute to their care. This approach is consistent with patient-centered, value-based care [71]. Given the high barriers to clinician participation in co-design sessions (e.g., scheduling demands; long working hours), brief (1 hour or shorter) web-based participatory design sessions may be preferable to longer in-person sessions [72]. Such online participatory methods have been proposed, e.g. the Hybrid Robotic Design Model, where design teams work in person at specific points of the design process, and other phases are conducted online [73].

Regarding **ethical** considerations, all papers with human participants, should include ethics approval disclosures and discussion. We are seeing a trend towards this, but there is still much room for improvement. Additionally, researchers should familiarize themselves with ethical guidelines. Unfortunately, as of yet, there is no large overarching and agreed upon set of guidelines for affective, social robotic and well-being applications, instead, researchers must asses their own work and use the applicable frameworks such as [28] for social robotics, [48] for perception in affective computing, and [49] for AI in clinical applications, to guide their research and discussions. Ethical implications must be considered at all stages of the study process, and stakeholders and their individual ethical responsibilities must be defined prior to conducting research [48]. We saw a focus on ethics on a personal level, i.e. dignity, and a lack of consideration for social and societal implications. As affective technology and robotics becomes increasingly prevalent these considerations are crucial for harmonious, safe, and fair integration of these systems [74].

Moreover, AI has come under scrutiny and much needed regulations are being put in place [50]. Although these laws regulate industry rather than research applications, researchers should not take this as an opportunity to skirt these rules. Likewise, with the move towards open source research and collaboration, any publicly available models or technologies that can be available for use by enterprises will be required to adhere to the regulations.

Emphasizing reproducibility, open-source practices, community collaboration, and the development of federated models is crucial and will enhance adherence to several agreed upon metrics of ethical guidlines including transparency, justice and fairness, non-maleficence, responsibility and privacy [74], [49]. Practices such as open science and pre-registration are vital for ensuring ethical and methodological rigor, especially given that our research aims to support human well-being, including individuals with clinical diagnoses. Adhering to the highest standards of empirical research in the field is paramount to uphold the integrity and impact of our work.

VII. Conclusion

This survey presents the evolution of the field of affective robotics for well-being over the last decade. By highlighting the past trends, present challenges, and future opportunities in the field of affective robotics for well-being, this survey aims to guide future researchers in tailoring their work based on the lessons learned and the envisioned trajectory of the field. We encourage researchers to consider the various implications of their work, including technical, design, and ethical considerations, to drive the development of affective robotics towards enhancing human well-being.

Acknowledgment

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