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Interactive Technologies for Emotion Regulation Training: A Scoping Review

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ABSTRACT

Emotion regulation is foundational to mental health and well-being. In the last decade there has been an increasing focus on the use of interactive technologies to support emotion regulation training in a variety of contexts. However, research has been done in diverse fields and no cohesive framework exists that explicates what features of such systems are important to consider, and what remains unknown which should be explored in future research. To address this gap, this paper presents the findings of a scoping review of 65 peer-reviewed papers. Through qualitative and frequency analysis we have analyzed the quality of published research, categorized the technologies that were used, reviewed their theoretical foundations, identified the opportunities that appear to provide unique benefits, and raised the challenges that require further exploration. Based on the findings we outline sensitizing concepts and considerations that researchers and designers may find useful for future designs and research. Where there are gaps in research, we propose gateways into non-HCI disciplines that may inform the design of future technologies and research designs for emotion regulation training.

1. Introduction

Emotion Regulation (ER) is the process by which individuals modulate their emotions, consciously or unconsciously (Gross, 1998). It is considered a key element of healthy psychological functioning (DeSteno, Gross, and Kubzansky, 2013) and has as much impact on life circumstances as IQ and family social status (Sanders and Mazzucchelli, 2013). In contrast, emotion dysregulation is failure to achieve emotion regulatory goals (Jazaieri, Urry, and Gross, 2013). Previous research proposed links between emotional dysregulation and different forms of psychopathology. More than one-third of young adolescents with Attention Deficit Hyperactivity Disorder (ADHD) would be considered to exhibit emotion dysregulation (Mennin et al., 2007). Different symptoms of anxiety disorders such as intensity of emotions and poor understanding of emotions are correlated with various aspects of emotion dysregulation (Mennin et al., 2007). While emotion dysregulation is positively correlated with diverse behavioral and personality disorders, it is considered to be a transdiagnostic characteristic with manifestations that vary across diagnoses (Bunford, WEvans, and Wymbs, 2015). Emotion dysregulation is implicated in more than half of the disorders in the Diagnostic and Statistical Manual of Mental Disorders (DSM) that need immediate attention (e.g., mood disorders and psychotic disorders) and all the DSM personality disorders and mental retardations (e.g., personality disorder and schizoid personality) (Gross and Levenson, 1997).

There are various therapeutic approaches that have been suggested to be beneficial to support ER training such as mindfulness-based stress reduction (Goldin and Gross, 2010), social-emotional learning school programs (Metz et al., 2013), cognitive behavioral therapy (CBT) (Aldao et al., 2014), and psychotherapy (Frederickson, Messina, and Grecucci, 2018). However, research shows the average delays in treatment for various mental health disorders exceeds 10 years (Wang et al., 2005). It is assumed that that the failure to seek treatment results in various reasons such the inability to recognize symptoms, lack of health care literacy (Thompson, Issakidis, and Hunt, 2008), personal or social stigma on mental care (Corrigan, Druss, and Perlick, 2014), and lack of access to mental health treatment (Goodwin et al., 2002).

Interactive technologies such as mobile apps, wearable technologies, tangible objects, and biofeedback and neurofeedback systems may offer unique opportunities to support ER training (Wadley et al., 2020). If shown to be effective, they could increase access and scalability of various therapeutic approaches that are currently conducted in clinics. It is too early to tell but there is potential that warrants research. For example, recent technological developments enable devices to measure

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physiological, neurological, and/or behavioral inputs. These measurements may be able to provide insight into emotional states that can aid ER training such as making invisible mental processes that are associated with emotion regulatory states, more visible (Antle et al., 2018). A recent review study by Dzedzickis et al., (2020) analyzed a broad range of technological platforms, ranging from lab-based sensors to consumer platforms that aimed at measuring emotional experience. Their findings suggest the potential of these emerging technologies to sense and infer aspects of emotional experience. Interactive technologies could be designed to use such bio-data to support and guide ER training through a range of forms of feedback and/or theoretical behavior change models (Dzedzickis, Kaklauskas, and Bucinskas, 2020). However, there are significant technical challenges in this field, especially in terms of accurately determining emotional experience. Apart from technical challenges there is also a research gap about how to design and deliver appropriate emotional representations that might support ER training. This challenge will remain significant even if future sensing technologies can enable accurate determination of emotional experiences. Representations of emotional states may utilize different modalities (e.g., haptic, visual, and audio) and forms (e.g., graphs and numbers, progress of a video game, movements of tangible objects). There is a plethora of approaches to ER training possible if one considers these options and different platforms (e.g., mobile devices, wearables, and tangibles). If well designed and validated, these interactive technologies may enable opportunities to learn and practice skills that are associated with ER in different ways including contexts of everyday experience.

Although interest in the field is quite new, there has been a considerable amount of research about technologymediated digital mental health, including ER support systems. For example, a recent study by Wadley et al. (2020), discusses digital ER as a promising cross-disciplinary field of research (Wadley et al., 2020). We conducted a scoping review to develop a better understanding of the kinds of technology-mediated ER support and training systems that have been developed in the field of human-computer interaction (HCI) research; that is, focusing on research about the kinds of interactions related to ER that may be enabled through interactive technology. Our review analyzes and summarizes research to date.We did not conduct a systematic review, since these tend to focus on domains where there are well-defined questions, and where evaluation studies such as randomized control trials (RCT) and field studies can be identified (Munn et al., 2018). Performing systematic reviews may be relevant when the motivation is to assess the effectiveness of a certain class of technology-mediated intervention. Previous systematic review studies have focused on specific categories of technologies for ER training where rigorous research methodologies can be found, such as video games (Pallavicini, Ferrari, and Mantovani, 2018, Villani et al., 2018) and mindfulness (Mikolasek et al., 2018). What is lacking is a scoping review that analyzes ways that HCI can be supported through interactive technologies targeting ER training broadly. The goals of our scoping review are to map the current state of the field in terms of opportunities and challenges identified to date, including sensitizing concepts, design considerations and research gaps in order to provide a cohesive overview and provide researchers information they can use to move the field beyond early-stage work (Arksey and O'Malley, 2005).

Our scoping review answers the following research questions:

1 *What type of interactive technologies have been used for ER training?*
2 *What types of users are interactive technologies for ER training designed for?*
3 *What are the theoretical models (of behavioral change) that underline interactive technologies for ER training?*
4 *What are the potential design opportunities created by interactive technologies for ER training?*
5 *What are the challenges faced when designing interactive technologies for ER training?*

Answering the questions above provides a baseline of current research in the field of interactive technologies for ER training while emphasizing the design opportunities to be explored and the challenges yet to be addressed through research. Based on the findings we outline sensitizing concepts and design considerations that researchers and designers may find useful for future designs and research. We conclude with two under-explored research areas that may warrant further exploration by the HCI community.

2. Related Work

In this section we highlight two topics that contextualize the current research. The first is an overview of what is meant by ER and ER training. The second topic is an overview of previous review papers in the field of HCI that drew attention to this quickly growing field of interactive technologies for ER training. The latter presents the motivation and contributions of previous review papers and illustrates the need for a broad scoping review in the field of interactive technologies for ER training.

2.1. Overview of Emotion Regulation

ER is the process of experiencing, expressing, and modulating emotions in the moment they occur. The process can be either automatic or controlled and involve either up-regulation or down-regulation of emotions (Gross, 1998). Emotion regulatory skills develop in childhood and are built up incrementally over time. In part, their development depends upon learning to regulate emotions through healthy attachment relationships between children and parents or caregivers (Engels et al., 2001). By early adolescence, with adequate support, sophisticated cognitive abilities that are associated with ER develop. In adulthood, individuals with strong ER skills understand that expressions of emotions are governed by social and contextual rules and they are able to regulate their own responses within the boundaries of these contexts (Gross and Muñoz, 1995). A key aspect of learning to regulate emotions involves identifying which environments are likely to trigger certain emotional experiences, how to recognize these experiences, and how to modulate the emotional experience and response (Gross and Muñoz, 1995).

One of the leading theories of ER is the Process Model of Emotion Regulation (Gross, 2015). In this model, Gross classified the process and strategies of ER by the stage at which the regulatory process occurred during the emotion-generation process. A recent study by Wadley et al. (2020) reviewed everyday use of screen-based technologies, analyzed the effect on the user's emotional state, and illustrated how such effects can be categorized by the different stages of the Process Model of Emotion Regulation (Wadley et al., 2020). For example, watching a video instead of performing work tasks was considered a situational selection strategy and performing the same activity instead of dealing with an emotional experience was considered an attentional deployment strategy. Wadley et al. (2020) referred to previous research that indicated the relation of various everyday interactions with technology on the user's emotional state (e.g., music listening (Randall and Rickard, 2017), video games (Villani et al., 2018) social media (Blumberg, Rice, and Dickmeis, 2016) and online shopping (Bui and Kemp, 2013)). In addition to the contribution of Wadley et al. (2020), a motivation of the current paper is to analyze technologies that that were deliberately designed for ER training.

Prevention science shows that certain ER skills can be developed and enhanced in later life stages through training. These methods range from school-based intervention programs such as social-emotional learning curricula (Weissberg et al., 2015), therapeutic interventions such as CBT (Hofmann et al., 2012), and various meditation sessions such as mindfulness (Farb, Anderson, and Segal, 2012). Social-emotional Learning (SEL) curricula are becoming widespread in schools and communities around the world as they have been shown to have positive effects on children's social-emotional-cognitive development and academic performance (Pellitteri and Smith, 2007). The SEL curricula enhances students' capacity to integrate cognition, affect, and behavior around social-emotional skills through various everyday contexts (Weissberg et al., 2015). CBT is a popular therapeutic approach that focuses on the cognitive factors that maintain mental disorders, emotional distress, and behavioral problems (Aldao et al., 2014). Within this approach the patient is an active participant in identifying and changing the maladaptive thoughts and behaviors that are associated with mental or behavioral symptoms. In the context of ER, CBT focuses on helping patients recognize physiological signs of anxiety or distress and providing behavioral strategies to cope with such symptoms (Hofmann et al., 2012). As opposed to CBT that is based on constant evaluation of experiences and memories, mindfulness is defined by attending to experiences in a non-judgmental manner (Farb, Anderson, and Segal, 2012). The variety of techniques used in mindfulness training includes deep breathing and focusing one's attention on inner or outer experiences (Antle et al., 2018). When practicing mindfulness, patients can disengage from cognitive judgment and behavioral responses to their environmental and physiological experience (Farb, Anderson, and Segal, 2012). While there is empirical support for the above strategies for ER training, most approaches have been time and resource intensive. Current developments in bio-sensors, mobile devices and other forms of interactive technologies open the door to examine the potential of technology-mediated approaches that might increase access, and decrease cost, of evidence-based ER training approaches.

2.2. *Previous Review Studies on Interactive Technologies for ER Training*

Designing technologies that are explicitly designed for ER training has been gaining much attention in various fields of study. The following section presents previous review papers in this quickly growing field. Review methodologies are used in different fields when it is challenging for a single researcher to read, evaluate, and synthesize the state of a current field. Review papers contribute to the field by providing a snapshot of the state of a current field, while analyzing different approaches to conduct research in that field, and they may draw attention to the need for future research in areas that are under-explored (Dyb and Dingsøyr, 2008).

Sanches et al. (2019) conducted a literature review on affective technologies in the context of mental health. Their analysis focused on the validation process of these technologies and the ethical considerations that guided the research presented in their review. Their findings raised the over-emphasis of previous technologies on producing data, without considering how it was beneficial for the user's wellbeing (Sanches et al., 2019). Howell et al. (2018) performed a critical analysis on emotional biosensing technologies. Their analysis leveraged standards from various fields to serve as a conceptual lens to unpack the design space of emotional biosensing technologies. Their findings emphasized the tendency to design emotional biosensing technologies in a way that promotes particular normative vision of a 'good life' and the constant striving for a 'better life' (Howell et al., 2018). While Sanches et al. (2019) and Howell et al. (2018) contributed to the field of HCI by raising ethical and social-technical questions that should guide future research in the field, they did not claim to provide researchers and designers with concrete design guidelines for designing future affective and emotional biosensing technologies (Howell et al., 2018, Sanches et al., 2019).

Other review papers focused on certain types of technological methods for ER training. Vasiljevic and Miranda (2019) conducted a literature review on electroencephalogram (EEG) brain-computer interfaces (BCI) in the context of video game-based ER training. Their findings indicated that most of the research in the field focused on quantitative aspects of the BCI system such as accuracy and performance. They raised the need for future research in the field to shed light on usability aspects such as quality of interaction and user satisfaction when interacting with such technologies (Vasiljevic and Miranda, 2020). Jerčić and Sundstedt (2019) conducted a systematic review of technologies for ER training in the context of serious games. Serious games in biofeedback-based ER training involve an interactive media that is coupled with physiological sensors that are used to monitor and modify the user's emotional state during gameplay. Their findings call for future research to carefully consider the standardization and methodological process, such as integrating sham-biofeedback condition (Jerčić and Sundstedt, 2019). While Vasiljevic and Miranda (2019) and Jerčić and Sundstedt (2019) provided a detailed review of the field of ER training, their scope focused on specific methods and they did not provide design guidelines and recommendations on how to design future technologies in this context (Jerčić and Sundstedt, 2019, Vasiljevic and Miranda, 2020).

Other review papers focused on certain types of activities that are associated with ER training. Mindfulness has been the focus of three previous review studies. Sliwinski et al. (2017) and Terzimehić et al. (2019) each presented an extensive review of technologies that support mindfulness and provided concrete design guidelines for future technologies in the field (Sliwinski, Katsikitis, and Jones, 2017, Terzimehić et al., 2019). Another review paper by Prpa et al. (2020) focused on technologies that used breathing awareness as a physiological process that is associated with ER. They provided a theoretical framework and design strategies for designing future technological systems for breath awareness and emphasized the need for a more conscious design practice that is informed by theoretical framing. While these papers contribute to the field by informing researchers and designers on how to approach the process of designing technologies for ER training, they did not claim to focus on more than one type of activity (Prpa et al., 2020).

To the best of our knowledge, only two papers have previously presented a review of a broad range of technologies and activities for ER training. Yoon et al. (2019) analyzed 36 publications and provided 17 strategies for ER training that can be used to enhance and prolong positive emotions, avoid negative emotions, and adapt to negative emotions (Yoon et al., 2019). In a late-breaking-work paper, Sadka and Antle (2020) presented a short review study based on 38 publications that emphasized usability and conceptual opportunities and challenges of technologies for ER training. They highlighted three directions for future research: technologies that provide emotional representations interpreted in light of the dynamic emotional experience of everyday activity, technologies that are designed for a single user and acknowledge the social influence of an emotional experience, and technologies that provide emotional representation that provides space for interpretation (Sadka and Antle, 2020). While the motivations of these papers are similar to the motivation of the current paper, in this paper we also explore theoretically grounded models of behavior change and/or ER training that have been used to design interactive systems and interventions, provide a synthesis of key design considerations and identify research gaps that offer opportunities for further design and empirical investigations, and provide pointers to other disciplines that can inform the conceptual challenges of the field of technologies for ER training.

3. Methods

3.1. *Scoping Review Protocol*

To answer our research questions, we followed the Preferred Reporting Items for Systematic Reviews and Metaanalysis Protocols for Scoping Reviews (PRISMA-Scr) (Arksey and O'Malley, 2005, Levac, Colquhoun, and O'Brien, 2010). Based on scoping review guidance, we identified our eligibility criteria, selected our source of evidence, charted the data, and summarized and reported the findings.

3.2. Eligibility Criteria

To identify relevant work we defined our search terms. First, we chose three terms related to technologies for ER training (“emotion-regulation” OR “self-regulation” AND “interactive technology”). After scanning the initial list of papers that came up from the search, we decided to perform an additional search that included the terms “stress” and “stress-regulation” as they are often used to describe the process of regulating anxiety: (“Interactive technology" AND one or more of “emotion-regulation” OR “self-regulation” OR “stress-regulation” OR “stress”).

Our motivation was to choose a search criterion that would yield a broad yet representative snapshot of the field of interactive technologies for ER training. As such, we decided to define broad terms (e.g., emotion-regulation or self-regulation and interactive technology) rather than searching for specific methods related to ER training (e.g., mindfulness, biofeedback, neurofeedback) or pathologies (e.g., dysregulation, post-traumatic stress syndrome, general anxiety disorder) or outcomes of ER training (e.g., well-being, relaxation). However, since these specific terms either fall under the umbrella of ER training (e.g., biofeedback) or are not relevant to our HCI focus (e.g., post-traumatic syndrome) we did not search on those exclusively. Our analysis, in which we used some of these specific terms for our search strategy, did not turn up additional relevant HCI papers but rather those that might be tangentially related, such as using biofeedback to enhance meditation, which is not ER training per se. We searched for papers that were published between January 1st 2009 and the day of the search (August 5th, 2021) and included the key terms mentioned above in title, abstract, and author keywords. We searched for papers that were published in two main HCI databases: Institute of Electrical and Electronics Engineers (IEEE) and Associate for Computing Machinery (ACM). We chose these databases as together they have a comprehensive collection of articles in the field of HCI. We decided to focus on these databases since the motivation in this scoping review was to provide a descriptive overview of papers that focus broadly on HCI style research and explore possibilities for interaction in this emerging and speculative field of study (Arksey and O’Malley, 2005). Note that including databases (e.g., PubMed) that likely contain evaluations of studies of the effectiveness of ER interventions would likely not provide the kind of information we required to address our research questions – which are design, technology and interaction focused, since they are likely to be clinical and/or therapeutic in nature. Future work should look at efficacy studies in a broader swath of databases once that work becomes more wide-spread. This search resulted in a total of 5,329 papers.

3.3. Selection of Sources of Evidence

We manually filtered the list of papers while keeping in mind their relevance to the research questions mentioned above (see Figure 1). The first author and a senior researcher with years of experience in ER technologies reviewed papers identified by keywords to determine suitability. By scanning titles and author keywords we excluded non-English papers, duplications, clinical trials, papers that did not present human ER, and review papers. Review papers that were found to be relevant were described in the Related Work section. Next, we read abstracts, scanned full texts, and assessed the publication quality. In this process we excluded papers that did not have an interactive respect with the user (no human-computer interaction), non-peer reviewed papers, and non-international publications. Finally, we read the design and method sections to remove papers that had no user study of any type (e. g., papers that only described designs but did not attempt to evaluate users’ experiences, usability, preferences of those designs) or no information on the underlying theory behind the design (i.e., theoretical model of behavior change).

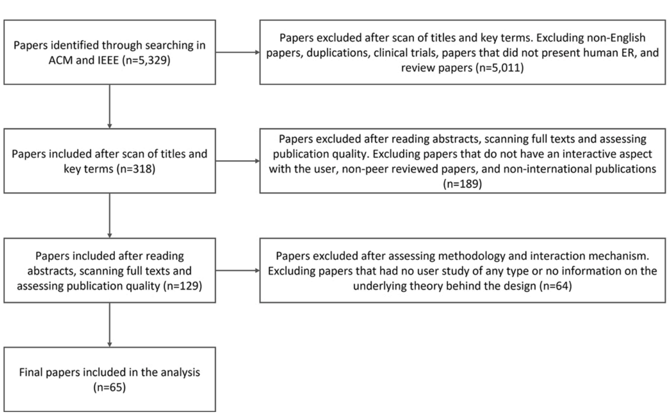

Fig 1. Selection of source of evidence.

In this paper, we defined a theoretical model as a theory-grounded model of behavior change that explains the expected relationship of causes and effects that is between the design features of a system and the intended interactional processes that support ER training. While previous research raised the need for literature reviews to evaluate not only what worked, but the theory of why and how an intervention worked (Arksey and O’Malley, 2005), we focused on the why behind the design of the intervention, in order to provide sensitizing concepts and considerations. In this early-stage research space, few papers included a rigorous evaluation of efficacy; however, we only included papers that, at minimum, provided theoretically grounded reasoning as to why the intervention was expected to be effective. Papers that did not include any description of a theoretical model were excluded in the sixth pass of the filtering process. The process of selecting sources of evidence and its results is visualized in Figure 1. At the end of the filtering process, 65 papers were found to be relevant for the purpose of this review.

3.4. Data Charting Process

We coded and analyzed the papers in three passes. In the first pass, to provide the context for interpreting the results of this scoping review, we assessed the quality of research studies. For each of the 65 papers we worked together to identify and assess the quality of the study based on the following: study methodology (e.g., formative design exploration, observation, experiment, and RCT), study context (e.g., lab, field), number of participants, constructs, measures, and fidelity of system. Low fidelity of system stands for low-fidelity or non-robust proof of concept prototype and high stands for robust system that could be deployed in a RCT or field study.

In the second pass we coded data for the first two research questions: (1) type of technology and (2) types of users. We classified the type of technology based on the following categories: technological platform, the context of activity, the input that was used to indicate an emotional state, the modality of the output, the level of abstraction of the output, and the timing and temporal window of the output. We analyzed the types of users based on their age and health condition related to challenges with ER.

In the third pass we addressed the next three research questions: (3) theoretical model (behavior change model), (4) opportunities, and (5) challenges. Answering these three questions involved inductively and iteratively working separately and coming together to define, revise and describe codes. Our final descriptions were as follows. We defined theoretical model as a theory of change that was used to justify one or more design features of the technological intervention that was proposed or hypothesized to support some form of ER training (Frechtling, 2007). We defined opportunities as potential ways that technologically mediated intervention and/or specific elements of their designs might contribute to enabling ER training. We defined challenges as reported usability issues, areas where justification was lacking or contradictory or simply unknown for choosing specific designs, and other potential design-related limitations of the technological systems. We did not include methodological and technical limitations as challenges as the purpose of the analysis was to conceptualize the different design features of interactive technologies for ER rather than their evaluation process or technical feasibility.

To develop codes that addressed the topics of research questions 3-5 (above), we followed an inductive and iterative approach. The two authors read random groups of 3-4 papers, proposed codes for each of the three topics based on the focus on HCI and ER. The coding process was done in repeated rounds, coding 3-4 papers each time that were randomly chosen. After each round, we met, compared our codes, and discussed. After analyzing and discussing the first 13 papers, the code categories and definitions stabilized for the three topics, reaching 100% agreement or consensus (O'Connor and Joffe, 2020). Then, the first author coded the remaining 52 papers. To establish intercoder reliability, the second author coded five new random papers. As there were no disagreements we ended our coding at this mutual and consensual interpretation of the data, and as such we do not report a numeric measure of 'objectivity' (O'Connor and Joffe, 2020). Then we followed an exploratory thematic analysis of the coded data, grouping similar or related codes into broader themes (Guest, MacQueen, and Namey, 2012). Again, we worked individually through the corpus of data and came together to compare the themes, keeping themes that reached consensus, and discussed until disagreements were reconciled. We chose an inductive method because we wanted to generate knowledge based on the data rather than being informed by previous review studies for our latter three research questions.

3.5. Methodological Limitations

A main limitation of our study is that our scope included HCI-oriented research in two databases (IEEE and ACM). By including other databases, for example, those covering clinical psychology or mental health, we may have found different user groups (e.g., clinical populations), themes around theoretical models, and opportunities and challenges that may have been related more to intervention logistics and efficacy than sensitizing concepts for design considerations.

Another limitation of this review is due to the relatively early stage of the HCI field of ER and interactive technology. As reported below, our analysis of research quality indicated that many studies involved design-oriented exploratory studies (rather than controlled experiments or RCTs) involving early-stage prototype systems (rather than robust systems that could be deployed in the field) and low numbers of participants. Such a trend towards design exploration rather than rigorous evaluation is typical for early-stage HCI research in a new domain area. Constructs, measures, and outcomes tended to focus on user perception or engagement with systems rather than targeted measures associated with ER skills. As a result, we present our findings cautiously in this light. For example, the design considerations section is largely speculative and descriptive rather than prescriptive, focusing on areas that our analysis of current research suggests may warrant further research. We also encourage HCI researchers who seek to understand more about intervention and efficacy-oriented studies to refer to publications from clinical, medical and/or mental health literature (e.g., (Mohr et al., 2017)).

In addition, in our analysis we did not focus on technical feasibility of the systems described in papers. For example, we did not assess the accuracy or precision of techniques used to collect and interpret bio-data in order to infer emotional states. We did not assess proposed systems in terms of their feasibility of being deployed in the world. Our work represents a snapshot of the kinds of interactive technologies and design features that have been proposed to support ER training, typically in non-clinical populations.

Moreover, papers that did not include the keywords that were presented under the search criteria sections were excluded. For example, there was little research on regulating positive emotions, and additional keywords might have turned up these kinds of papers. In addition, our criteria excluded papers without any form of theoretical grounding or user study; we likely excluded papers that might have provided interesting insights, for example, design fictions or other forms of speculations. As a result of these scoping review methodological limitations, our analysis and findings are not comprehensive. Since our motivation was to provide the HCI community better understanding of the field from a design perspective, our results meet this goal and provide a broad picture of the current state of HCI research from a design and interactional perspective.

4. Results

This section presents the findings of a scoping review on the topic of interactive technologies for ER training. We present high-level descriptive statistics based on our research questions. Where codes are mutually exclusive and exhaustive (add up to 100% of the papers), we display results with pie charts which are detailed in percentage (e.g., user demographics). Where a study or paper may be coded with more than one category (e.g., for technological platform, a single system might involve more than one platform, such as both a wearable and mobile) we use bar charts which are detailed in frequency (e.g., technological platform). We summarize the findings from our quality assessment to provide context for interpreting the rest of our findings, in particular our identification of the opportunities and challenges, as well as the design considerations. In these sections, we based the strength of our claims on the level of quality we found across and within studies. For example, in the few cases where evidence includes RCTs or controlled experiments in which results validate ER-specific measures we make stronger claims than in cases where studies were exploratory and/or evaluated using indirect measures of ER (e.g., engagement, satisfaction). See Appendix for paper analysis.

4.1. Quality of Research

Our analysis of the quality of research studies indicated that 15 of the 65 studies were formative design explorations, 18 were observational studies, 28 involved controlled experiments, and 4 were RCTs. See Appendix for quality of research analysis.

In the 15 formative design explorations, researchers explored the usability (e.g., SUS survey (Díaz-Escudero et al., 2018)), user perception (e.g., self-report of emotional awareness (Huang, Tang, and Wang, 2015)) and/or engagement (e.g., score of the activity (Crepaldi et al., 2017)) with different design elements (e.g., strength and rhythmic patterns of tactile stimulation (Choi and Ishii, 2020)). Ten (10) of these studies used low fidelity systems (e.g., (Sabinson, Pradhan, and Green, 2021)) and 5 used medium fidelity systems (e.g., (Snyder et al., 2015)). Nine (9) studies were conducted in lab (e.g., (Jingar and Lindgren, 2019)), 6 in the field (e.g., (Huang, Tang, and Wang, 2015)) and participant numbers ranged from 1 (Paratore, 2020) to 30 (Crepaldi et al., 2017) with an average of 12 participants.

In the 17 observation studies, researchers explored the impact of a prototype or a system on measures related to emotional state such as the Emotion Regulation Questionnaire (Lobel et al., 2016), Theta/low Beta ratios (e.g., (Mandryk et al., 2013)), and heart-rate variability (e.g., (Yu et al., 2018)). Eleven (11) of these studies used low fidelity systems (e.g., (Pham et al., 2021)), 2 used medium fidelity systems (e.g., (Pina et al., 2014)), and 4 used high fidelity systems (e.g., (Ding et al., 2021)). Twelve (12) studies were conducted in lab (e.g., (Zhou, Murata, and Watanabe, 2020)), 16 in the field (e.g., (Sanches et al., 2019)) and participant numbers ranged from 2 (Elsborg, Bruun, and Jensen, 2020) to 198 (Bakker and Rickard, 2018) with an average of 30 participants.

In 29 controlled experimental studies, researchers investigated the causes and effects between system features and engagement and/or measures related to ER. Seven (7) experimental studies used a within-subject experimental design (e.g., (Shamekhi and Bickmore, 2018)), 17 were a between-subject experimental design (e.g., (Costa et al., 2019)), and 5 used mixed-subject experimental design (e.g., (Paredes et al., 2014)). Twenty-two (22) studies were conducted in lab (e.g., (Sas and Chopra, 2015)), 6 in the field (e.g., (Fage et al., 2019)). Five (5) of these studies used low fidelity systems (e.g., (Umair et al., 2021)), 17 used medium fidelity systems (e.g., (Semertzidis et al., 2020)), 6 used high fidelity systems (e.g., (Wang, Fischer, and Bry, 2019)). Participants numbers ranged from 10 (Semertzidis et al., 2020) to 112 (Oehler and Psouni, 2019) with an average of 36 participants. Measures related to ER were either direct or indirect. Direct measures evaluate whether ER skills are learned and can be implemented (e.g., (Antle et al., 2019)). Indirect measures evaluate outcomes that are correlated to ER skills such as physiological (e.g., (Wang, Parnandi, and Gutierrez-Osuna, 2017)) and neurological (e.g., (Sas and Chopra, 2015)) data, behavioral measures such as performance on a cognitive consuming task (e.g., (Moraveji, Adiseshan, and Hagiwara, 2012)), awareness to an emotional experience (e.g., (Ghandeharioun and Picard, 2017)), and various self-report measures such as Positive and Negative Affect Scale and Player Experience of Need Satisfaction scale (e.g., (Reinschluessel and Mandryk, 2016)). Examples of features that were evaluated are integration of bio/neurofeedback mechanisms or machine learning (ML) algorithms that are adaptive to users' data indicating emotion regulatory state, compared to baseline conditions (Paredes et al., 2014), various modalities of output for emotional representation such as light and vibration (Frey et al., 2018), and different types of gamification feedback mechanisms such as partial and continuous reinforcement schedules (Parnandi and Gutierrez-Osuna, 2018).

In 4 RCTs, researchers claimed to investigate the efficacy of interventions. We assessed the risk of bias of each of the 4 papers through the Cochrane tool (Eldridge et al., 2016) and found that the overall risk-of-bias judgment of three of the papers "raised some concerns" (Lloyd, Brett, and Wesnes, 2010, Smyth and Heron, 2016, Wells et al., 2012) and one of the papers raised "high risk of bias" (Scholten et al., 2016). Efficacy was measured by measures such as Signal-detection Theory Index of Sensitivity (Lloyd, Brett, and Wesnes, 2010), Spence Children Anxiety Scale (Scholten et al., 2016), cortisol levels (Smyth and Heron, 2016), and State-Trait Anxiety Inventory (Scholten et al., 2016), again focusing on indirect measures. Two of the 4 studies were conducted in lab (Wells et al., 2012) and two in the field (Scholten et al., 2016). One study used a medium fidelity system (Wells et al., 2012) and 3 used high fidelity systems (e.g., (Lloyd, Brett, and Wesnes, 2010)). Participant numbers ranged from 38 (Lloyd, Brett, and Wesnes, 2010) to 114 (Scholten et al., 2016) with an average of 72 participants.

Based on the above assessment of the quality of evidence it is evident that findings from most papers in the field of interactive technologies for ER training are still relatively speculative (non-causal) and tend to focus on self-report of indirect measures of ER such as engagement, emotional awareness or state, and/or inferences from physiological data about emotional states rather than direct measures of the improved ability to use ER skills, which can be used to establish efficacy. Consequently we take a descriptive approach to reporting findings and are speculative in how we address the opportunities and challenges revealed in our analysis. We also present design considerations as largely speculative, but highlight considerations based on evidence that was more rigorous in contrast to considerations based on early-stage research results (i.e., formative design explorations and observations studies) that were evaluated on a relatively small number of participants, and measured indirect measures, which may warrant more research.

4.2. *RQ 1: What Types of Technologies are Used for ER Training?*

We analyzed the types of technology in terms of the platform that was used, the type of activity the technology was designed for, the input that was used to indicate an emotional state, the modality of the output that was used to deliver the feedback, the level of abstraction of the feedback, and the output Timing and Temporal Window of the feedback. Careful analysis of the different types of technologies (based on the categories above) revealed that there were no insights in terms of frequent patterns and/or under-explored design choices of previous technologies for ER training. See Appendix for type of technologies analysis.

4.2.1. *Technological Platform*

The review indicated that screen-based platforms such as personal computer (PC) (e.g., (Crepaldi et al., 2017)), tablets (e.g., (Antle et al., 2019)), and mobile phones (e.g., (Bakker and Rickard, 2018)) were used in 39 papers. Wearable platforms such as smartwatches (e.g., (Zheng and Motti, 2017)) were used in 17 papers. Tangibles such as fidgets (Liang et al., 2018) and interactive dolls (Slovák et al., 2018) were used in six papers, smart home and cars were used in six papers (e.g., (Balters et al., 2020)), VR was used in two papers (e.g., (Cavazza et al., 2014)), and a robot was used in one paper (Pham et al., 2021) (see Fig. 2).

4.2.2. *Context of Use*

ER training were framed around five intended contexts: Fifty-five percent (55%) of the technologies were designed for everyday activity such as classroom context (e.g., (Fage et al., 2019)), and car driving (e.g., (Zepf et al., 2020)), 21% of the technologies were designed for video games such as multiplayer video games (Khong et al., 2014) and car racing games (Wang, Parnandi, and Gutierrez-Osuna, 2017). The rest of the technologies were designed for meditation sessions (e.g., (Shamekhi and Bickmore, 2018)), lab contexts (e.g., (Wells et al., 2012)), and craft activities (e.g., (Lee and Hong, 2017)) (see Figure 3).

4.2.3. *Emotion-based Input*

Emotion-based input refers to the type of data that were used to indicate an emotional state. The reviewshowed that 33 papers used biological data such as respiration (e.g., (Parnandi and Gutierrez-Osuna, 2018, Pisa et al., 2017)), heart-rate variability (e.g., (Lobel et al., 2016, Zhou, Murata, and Watanabe, 2020)) and skin conductance (e.g., (Parnandi and Gutierrez-Osuna, 2015)) to indicate users' emotion regulatory state. Twelve (12) papers used neurological input such as EEG (e.g., (Cavazza et al., 2014)). The rest of the technologies used self-report (e.g., (Smyth and Heron, 2016, Springer, Hollis, and Whittaker, 2018)), behavioral input, (e.g., (Crepaldi et al., 2017)), data about physical location (e.g., (Paratore, 2020)), tangible interaction during interaction with a fidget (Liang et al., 2018), and body movement (e.g., (Rooij and Jones, 2015)) (see Figure 4).

4.2.4. *Output Modality*

Output modality refers to the sensory channels through which the output is perceived by the user. While many technologies used multimodal feedback (e.g., audio and visual displays in a video game), we included in this analysis only output modalities that were modified based on the emotion-based input. Forty-four (44) papers used on-screen visual modality as an output, such as PCs (e.g., (Lloyd, Brett, and

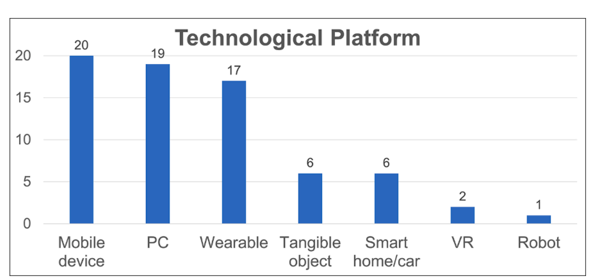

Fig. 2. Graph chart with the technological platform. Paper examples for technologies that were based on mobile devices (e.g., Cochrane et al., 2020,), PC (e.g., Schneeberger et al., 2021), wearable (e.g., Roquet and Sas, 2021), tangible object (e.g., Jingar and Lindgren, 2019), smart home/car (e.g., Cochrane et al., 2021), and a robot (Pham et al., 2021).

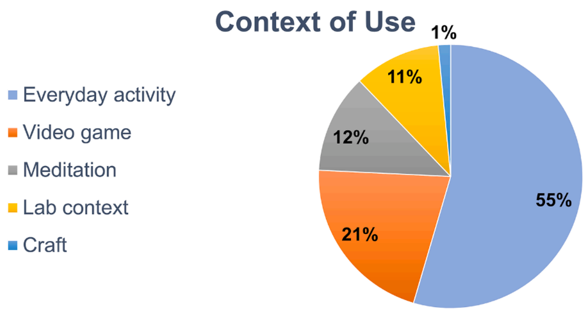

Fig. 3. Pie chart with context of use. Paper examples for technologies that were designed for everyday activity (e.g., Zhou, Murata, and Watanabe, 2020), video games (e.g., Abdullah Zafar, Ahmed, and Gutierrez-Osuna, 2017), meditation (e.g., Shamekhi and Bickmore, 2018), lab context (e.g., Yang et al., 2018), and craft (Lee and Hong, 2017).

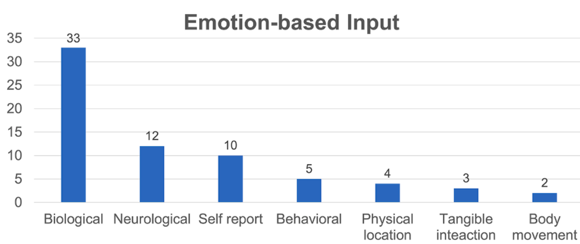

Fig. 4. Graph chart with emotion-based input. Paper examples for technologies that were designed based on biological input (e.g., Choi and Ishii, 2020), neurological input (e.g., Khong et al., 2014), self report (e.g., Bakker and Rickard, 2018), behavioral input (e.g., Springer, Hollis, and Whittaker, 2018), physical location (e.g., Sanches et al., 2019), tangible interaction (e.g.,Slovák et al., 2018), and body movement (e.g., Niksirat et al., 2019).

Wesnes, 2010)), tablets (e.g., (Slovák et al., 2016)), and mobile phones (e.g., (Carlier et al., 2019)). The rest of the technologies use audio (Ghandeharioun and Picard, 2017, Sas and Chopra, 2015), haptic modality in the form of vibrations (e.g., (Choi and Ishii, 2020)), tangible interaction with a physical object (Stangl et al., 2017), and light not from a screen source (e.g., (Liang et al., 2018, Yu et al., 2018)) (see Figure 5).

4.2.5. *Output Level of Abstraction*

Technological interventions varied in terms of the level of abstraction of the output that was used to represent an emotional state (see Figure 6). Thirty (30) technological interventions provided concrete feedback. Using concrete representation can support the interpretation of symbolic representations of abstract processes (Antle and Wise, 2013). We found that designers used concrete representations such as explicit behavioral suggestions (e.g., (Fage et al., 2019)), numbers (e.g., (Moraveji, Adiseshan, and Hagiwara, 2012)), graphs (e.g., (Yang et al., 2018)), and explicit cues during a video game in the form of penalty or reward points (Antle et al., 2019). Twenty (20) papers used metaphors to indicate the efficiency and progress of an emotion regulatory process. Metaphoric representation is used to convey abstract concepts through unconscious metaphorical elaboration (Antle and Wise, 2013). Designers used metaphoric representations such as use of colors to convey an emotional state (Snyder et al., 2015), vertical vibration patters to indicate a respiration rate (Balters et al., 2020), and metaphors from the natural worlds such as increasing speed of a race car during a video game (i.e., the faster the car goes the better the emotion regulatory process) (Khong et al., 2014), the use of colors to convey an emotional state (Snyder et al., 2015), and metaphors from the natural world such as rain, flowers, fire (Bermudez i Badia et al., 2018), and growth patterns of trees (Yu et al., 2017). Analogies were used in 15 technological interventions. Analogical representations are based on similarity between elements of the abstract concept and their representation. Designers used analogical representation in different ways such as clearing the screen from overlay texture is like focusing on a video game (Mandryk et al., 2013) and vibration patterns on the skin are like physiological signs such as heart rate (e.g., (Choi and Ishii, 2020)) and respiration (e. g., (Frey et al., 2018)). Four (4) technological interventions used abstract representations that required users to make sense of their emotional state explicitly, such as reflecting on shapes of clay (Lee and Hong, 2017).

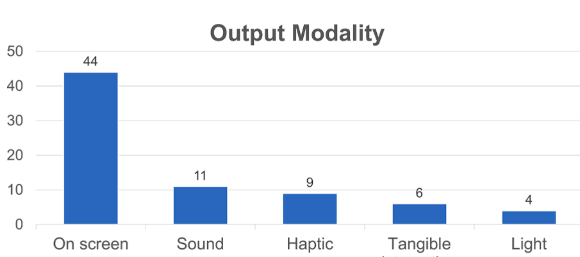

Fig. 5. Graph chart with output modality. Paper examples for technologies that used screen-based output modality (e.g., Parnandi and Gutierrez-Osuna, 2018), sound modality (e.g., Ghandeharioun and Picard, 2017), haptic (e.g., Balters et al., 2020), tangible interaction (e.g., Rooij and Jones, 2015), and light modality (e.g., Liang et al., 2018).

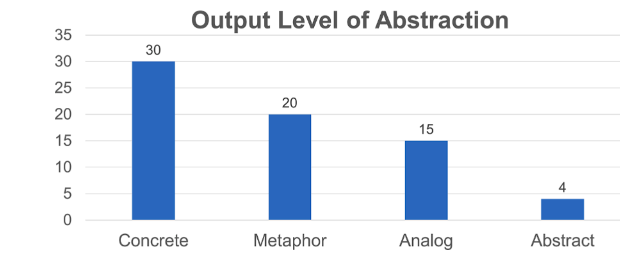

Fig. 6. Graph chart with output level of abstraction. Paper examples for technologies that used concrete representation (e.g., Shamekhi and Bickmore, 2018), metaphoric representation (e.g.,Cavazza et al., 2014), analogical representation (e.g., Choi and Ishii, 2020), and abstract representation (e.g., Lee and Hong, 2017).

4.2.6. *Output Timing and Temporal Window*

Output timing refers to when the feedback was provided in accordance with the input that was used to record the emotional state of the user (See Figure 7). Fifty-three (53) technologies provided immediate feedback (e.g., Smyth and Heron, 2016). Five (5) technologies provided longitudinal feedback. Bakker and Rickard (2018) provided users a 'mood diary', where users reflected upon their emotional experience over time, measured by self-report (Bakker and Rickard, 2018). Five (5) technologies provided real-time and longitudinal feedback. For

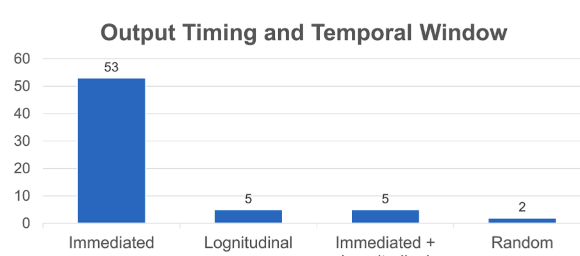

Fig. 7. Graph chart with output level of output timing and temporal window. Paper examples for technologies that used immediate feedback (e.g., Li et al., 2021), longitudinal feedback (e.g., Bakker and Rickard, 2018), immediate and longitudinal feedback (e.g., Díaz-Escudero et al., 2018), and random timing of feedback (e.g., Oehler and Psouni, 2019).

example, Sanches et al. (2019) provided users with real-time data based on their bodily reaction. In addition, the system invited users to reflect upon their bodily reactions over different time frames (Sanches et al., 2019). Two technologies provided feedback in random timing as part of partial reinforcement feedback (e.g., (Parnandi and Gutierrez-Osuna, 2018)). Temporal window refers to the temporal resolution in which the output was computed based on the input. Thirty-nine (39) technologies used a discrete threshold such as changed physiological measures (e.g., (Crepaldi et al., 2017)). Nineteen (19) of the technologies provided continuous emotional representation such as changing sound based on real-time respiration (e.g., (Niksirat et al., 2019)). Seven (7) technologies did not provide details of the temporal window, or temporal window was not relevant in the technological intervention.

4.3. *RQ 2: What Type of Users are Technologies for ER Designed for?*

We analyzed the types of users on two levels: age and health condition. We chose these levels since different developmental stages and health conditions require different types of support for ER training. Our analysis revealed that 81% of the technologies were designed for adults (e.g., (Semertzidis et al., 2020)) and 19% were designed for children (e.g., (Crepaldi et al., 2017)) and adolescents (e.g., (Scholten et al., 2016)). When analyzing the health condition within each age group we found that only 5% of the technologies designed for adults were designed for non-healthy adults (e.g., highly stressed adults). In contrast, 79% of the technologies that were designed for adolescents and children were designed for non-healthy adolescents and children (e.g., ADHD, autism spectrum disorders, fetal alcohol spectrum disorders, anxiety) (see Figure 8). See Appendix for type of user analysis.

4.4. *RQ 3: What are the theoretical models (of behavior change that underline interactive technologies for ER training?*

To answer this research question our analysis focused on identifying the theory of behavior change related to ER that was described in the paper and/or used to structure the design components that underlined the intervention (Frechtling, 2007). Our analysis revealed four categories of theoretical models (see Figure 9). See Appendix for theoretical model analysis.

4.4.1. *Biofeedback (BFB and Neurofeedback (NFB*

Forty-four (44) technological interventions used data from physiological or neurological state as the basis for inferring emotional state, which was displayed to the user as feedback. This model assumes that feedback can enable the user to implicitly or explicitly regulate their emotional state (e.g., reduce stress by viewing and trying to reduce heart rate variability). In a field RCT with 39 children with ADHD, Lloyd et al. (2010) showed that a 6-week BFB intervention was successful in improving cognitive functioning through various measures such as the Cognitive Drug Research System (Lloyd, Brett, and Wesnes, 2010). Our analysis revealed two strategies that were used in designing technologies under this theoretical model. Sixty-three percent (63%) of the technologies under this theoretical model encourage users to reach a target physiological state based on positive or negative feedback (e.g., (Parnandi and Gutierrez-Osuna, 2015)). They assume that users should regulate their emotions towards reaching a target that was provided by the system through operant conditioning. In this strategy, specific physiological or neurological states are rewarded, either continuously or intermittently, with some sort of feedback. The rest of the technologies under this theoretical model (37%) were designed to raise the user's awareness of their current physiological signs that are associated with ER through feedback (e.g., (Sanches et al., 2019)). This strategy assumes that through raising awareness to changing physiological signs, users can modify their emotional experience.

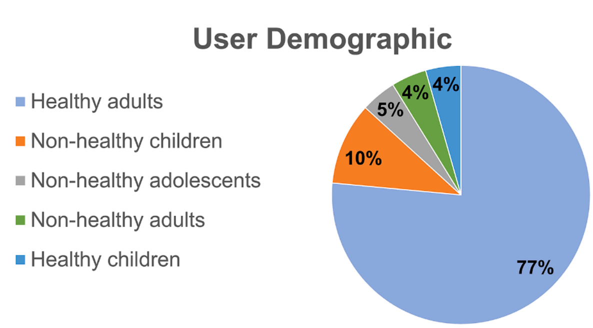

Fig. 8. Pie chart with user demographic. Paper examples for technologies that were designed for healthy adults (e.g., Balters et al., 2020), non-healthy adults (e.g., Paratore, 2020), healthy children (e.g., Stangl et al., 2017), non-healthy children (e.g., Crepaldi et al., 2017), and non-healthy adolescents (e.g., Fage et al., 2019).

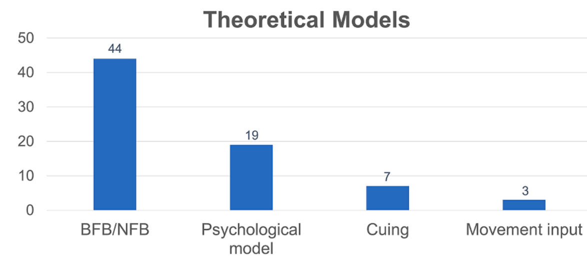

Fig. 9. Graph chart with theoretical models. Paper examples for technologies that were designed based on BFB/NFB (e.g., Cavazza et al., 2014), psychological models (e.g., Bakker and Rickard, 2018), cuing (e.g., Zhou, Murata, and Watanabe, 2020), and motor-based input (e.g., Niksirat et al., 2019).

4.4.2. *Psychological Therapeutic Models*

Nineteen (19) technological interventions were based on psychological models used in therapeutic contexts. These technologies are informed by evidence-based strategies that are usually used in the context of psychological therapy and psychological informed workshops. Under this theoretical model, 72% of the technological interventions were based on Cognitive Behavioral Therapy (CBT) (Pina et al., 2014). The core aspects of CBT build on the notion of supporting patients to think about their thinking and consciously identify patterns that have a negative impact on their emotions and behaviors. After being made aware of negative thoughts, patients are encouraged to actively change their thoughts and behaviors (Beck, 1997). In a field RCT with 90 highly stressed adults, Smyth Heron (2016) showed that ML-based reminders for CBT interventions resulted in lower levels of cortisol and participants reported less stress than non-tailored, random reminders (Smyth and Heron, 2016). The rest of the technological interventions under this theoretical model (28%) were designed based on various psychological models such as the dual pathway model (Crepaldi et al., 2017), emotion-focused therapy (Jingar and Lindgren, 2019), attachment-theory (Oehler and Psouni, 2019), and positive psychology (Paredes et al., 2014).

4.4.3. *Static Target Cuing*

In a more speculative approach, seven (7) technological interventions provided users feedback that was based on target-beneficial emotion regulatory state. Unlike other interventions, technological interventions under this theoretical model did not represent the user's emotional state, but rather provided users with a target that represented desired emotional state and provided cues to encourage them to reach that state. This process builds on the notion of interpersonal touch (Gallace and Spence, 2010), empathy (Fukushima, Terasawa, and Umeda, 2011), increase of conformity (Dong, Dai, and SWyer, 2015), and physiological synchronization (Keller, Novembre, and Hove, 2014). Through a lab RCT with 46 musicians, Wells et al. (2012) showed that a single session of slow breathing, regardless of adaptive biofeedback, is sufficient to reduce physiological arousal in the context of social stress (Wells et al., 2012). Similarly, in a between-subject experimental design with 72 participants Costa et al. (2019) evaluated BoostMeUp, a smartwatch intervention that was designed to "override user's self-perception of their heart rate" by providing slower haptic feedback (Costa et al., 2019). Their findings showed that slow haptic feedback during a cognitively demanding task decreased their anxiety measured by State-Trait Anxiety Inventory, increased their heart rate variability and performance in the task as opposed to fast haptic feedback.

4.4.4. Using Movement to Regulate Emotions

Three technological interventions built upon the association of the sensory-motor system with emotional experiences. This underexplored model assumes that certain movements may be used to regulate various emotional states. This association is considered innate as it is noticeable in newborns' ability to express and interpret emotions (Leventhal, 1984). In a mixed-subject experimental design with 52 participants, Niksirat et al. (2019) evaluated a mobile application that tracked the user's repetitive body movement as an input for their level of attention during a mindfulness training session (Niksirat et al., 2019). Their technological intervention was designed based on the Relaxation-Response Theory and enhanced slow and repetitive movements to elicit relaxation (Benson and Goodale, 1981). Their findings indicated that including repetitive movements in a mindfulness session was found to be more effective than guided meditation apps in improving physical balance, attention, mindfulness, mood, and well-being measured by a set of self-report questionnaires. A more speculative approach used physical interaction with tangible modality to express emotions. Through a field observation study with 16 participants, Lee and Hong (2017) presented an approach for representing and expressing emotions through tangible interaction with a plasticine clay. They observed that "tangible modality afforded users an opportunity to embody their emotions in a variety of forms" (Lee and Hong, 2017).

4.5. RQ 4: What are the Potential Design Opportunities Created by Interactive Technologies for ER Training?

The thematic analysis revealed 14 opportunities that were subsequently arranged into the following five high-level themes (see Table 1).

4.5.1. Access

Access refers to the opportunity of increasing access during everyday moments to supports for ER through technological systems. The review showed that technologies that were designed for use during everyday activity may offer "constructive in-the-moment support" during everyday stressful situations (Slovák et al., 2018). Huang et al. (2015) raised the potential of sensing location and contextual situations in real life as important triggers for emotion (Huang, Tang, and Wang, 2015). In a mixed-subject experimental design with 112 participants, Oehler and Psouni (2019) added that mobile technologies offered opportunities to influence human behavior as they can be integrated in daily life within different locations (Oehler and Psouni, 2019). More early-stage studies explored this opportunity with various prevalent devices such as wearables (e.g., (Costa et al., 2019)), tangibles (e.g., (Liang et al., 2018)), and mobile devices (e.g., (Niksirat et al., 2019)) that can sense, in a non-invasive way, behaviors or physiological processes that are associated with ER.

Table 1
Opportunity themes

High-level theme	Design opportunities
Access	- Emotional training during everyday activity
	- Using prevalent devices
Engagement	- Gamifying ER training
	- Structuring ER training as storytelling
	- Providing external motivation
	- Multimodal feedback
Plethora of Approaches	- Feedback that is easy to interpret and understand
	- Feedback that provides space for interpretation
	- Longitudinal feedback
	- Opportunities for reflection
Personalization	- Enable user customization
	- Using ML to learn and predict an emotional state
	- Coupling subjective and objective emotional experience
Social Interaction	- Social emotional sharing and support

4.5.2. Engagement

Engagement refers to the diverse opportunities offered by interactive technologies for engaging users with ER training. While user's engagement is important in the context ER training, measuring user engagement does not provide evidence about the efficacy of a system. The review indicated that there are diverse approaches to engage users with ER training. Gamification was a prevalent method that increased user's engagement through positive (e.g., (Parnandi and Gutierrez-Osuna, 2015)) or negative reinforcement (e.g., (Mandryk et al., 2013)). In a between-subject experimental design with 53 participants, Reinschluessel and Madnryk (2016) showed that positive reinforcement was more effective in encouraging players to keep their brain activity regulated when playing neurofeedback games (Reinschluessel and Mandryk, 2016). Engagement and motivation were measured by the Positive and Negative Affect Scale, Player Experience of Need Satisfaction scale, and Intrinsic Motivation Inventory. Another method was storytelling. Slovák et al. (2016) designed a digital storytelling system that was framed around a "grumpy Pirate Harrdy searching for his treasure". The narrative motivated children to "re-live their feelings" in a safe environment with their caregiver (Slovák et al., 2016). Díaz–Escudero et al. (2018) presented a mobile application that was based on external authority. Their technology provided users with Autism Spectrum Disorders (ASD) "step-by-step coaching methods of emotional self-regulation" (Díaz-Escudero et al., 2018). Multimodal representation such as visual and audio representations of an emotional experience were used to engage users during the interaction with the technology towards fostering "more effective emotional regulation strategies" (Bermudez i Badia et al., 2018).

4.5.3. Plethora of Approaches for Emotional Representation

This opportunity describes the many ways there are to represent emotional states to end-users. At this time, while there is little evidence of best practices, there are many forms of representations that can be explored in future research, likely each with advantages and disadvantages depending on the context. Cumulative feedback has a clear mapping that made it easy to interpret and understand what a desired mental state is. In some interventions, increased numbers were used to indicate successful emotion regulatory states. For example, in a field mixed-subject experimental design with 20 children, Antle et al. (2019) encouraged children to earn tokens, indicating sustained relaxation state. Earning tokens indicates more sustained relaxation state (Antle et al., 2019) (i.e., 'higher' numbers that indicate a good regulatory mental state). In contrast, other interventions used increased numbers to indicate unsuccessful emotion regulatory states. For example, in a between subject experimental design with 33 participants, Wang et al. (2017) added texture overlay during a video game, indicating physiological arousal. More overlay texture indicated less emotionregulatory physiological responses (Wang, Parnandi, and Gutierrez-Osuna, 2017) (i.e., 'higher' numbers indicated a poor regulatory mental state). In general, technologies that provide cumulative feedback are designed to help users shift from a stressful and unregulated state to a relaxed and regulated state.

A more speculative technological approach provides space for interpretation. In a field observation study with 23 participants, Sanches et al. (2019) designed a mobile application that represents users' levels of skinconductance in a way that "evokes multiple interpretations in an on-going process of co-constructive making of meaning" (Sanches et al., 2019). Other technologies used tangible ways to represent an emotional experience. In a formative design exploration, Lee and Hong (2017) presented an approach for representing and tracking emotion through tangible interaction with plasticine clay and a diary. They mentioned that the abstraction of emotions through different shapes of clay represented a "nuance of emotion with a shape that was not accurately defined" that gave participants opportunities to reflect upon their emotional experience (Lee and Hong, 2017). Finally, some technologies provided longitudinal emotional representation. In a pre-post survey sample with 198 participants, Bakker and Rickard (2018) showed that a mobile application that presented emotional data over time, based on daily-mood surveys, decreased depression and anxiety and increased mental well-being measured by self-report measurements (e.g., Generalized Anxiety Disorder Scale and Social Desirability Scale) (Bakker and Rickard, 2018).

4.5.4. *Personalization*

Personalization refers to the opportunity to adapt design features to the changing needs of users as they ER. Technologies that enable user customization are scarce. In a field mixed-subject experimental design with pre-post and follow-up direct measures of ER ability with 20 children, Antle et al. (2019) integrated a customization feature into a neurofeedback game for children. This feature enabled the intervention to meet the changing needs of individuals in real time and increased motivation by setting achievable goals (Antle et al., 2019). Through a within-subject experimental design with 36 participants Miri et al. (2020) emphasized the importance of personalizing vibrotactile interventions for ER. Based on their comparison of personalization features with physiological data related to anxiety, they raise the importance of personalizing emotional feedback not as a one-time procedure, but as a continuous process that can capture the dynamic influences of both inward and outward processes on an emotional state (Miri et al., 2020). Other ways to personalize ER training use machine-learning to analyze and predict an emotional state. Paredes et al. (2014) used a machine-learning based intervention that provided personalized stress reduction strategies based on self-report and sensory features that were collected through mobile phone usage, such as GPS location and calendar record (Paredes et al., 2014). While many of the technologies use physiological data to infer an emotional state, few couple subjective forms of data and objective measurements to enable personalized emotional feedback that is sensitive to situational emotional state (e.g., (Kocielnik et al., 2013)).

4.5.5. *Social Interaction*

While most technologies for ER training were designed for an individual user, some leverage social interaction as a means to support ER. Shamekhi et al. (2018) presented a humanoid conversational agent that acted as a "virtual meditation coach" through mirroring users' respiration during a meditation session. Other technologies were designed for sharing social emotional experiences over distance. For example, Huang et al. (2015) provided users the opportunity to share their emotional experience with their friends or the general public, with or without their identity (Huang, Tang, and Wang, 2015). A different approach focused on enhancing social emotional experience between people who were co-located in the same space. Snyder et al. (2015) presented an interactive ambient lighting system that responded to biosensor input related to an individual's current level of arousal. Their findings showed that implementing such a technology in a social context enabled users to validate and acknowledge the feelings of others and "adjust themselves to try to optimize their shared experience" (Snyder et al., 2015). Similarly, Slovák et al. (2016) designed a digital storytelling system that was designed to "promote the parental involvement and support" for children's ER skills. Through the storyline, they "set the scene for a more direct parent-child interaction" (Slovák et al., 2016). In a RCT, Lloyd noted that parents who practiced ER skills along with their child reported personal benefits themselves (Lloyd, Brett, and Wesnes, 2010). Designing technologies that enable sharing emotional experience and moments for social-emotional support warrants further study as means to induce behavioral change.

4.6. *RQ 5: What are the Challenges Faced when Designing Interactive Technologies for ER Training?*

The thematic analysis revealed eight challenges that were subsequently arranged into the following three high-level themes (see Table 2):

4.6.1. *From Emotional Data to Emotional Representation*

While there has been significant investment in deterministic and diagnostic methods to detect and infer emotional state, little is known about how to provide appropriate emotional feedback that is beneficial for ER training. While this vacuum offers researchers and designers the freedom to choose among various ways to represent an emotional experience, it also poses a challenge in terms of determining best practices. Technologies that provided concrete feedback that inferred 'good' and 'bad' emotional state, or an emotion regulatory process often overlooked the contextual emotional state of the user (e.g., (Díaz-Escudero et al., 2018)). On the other hand, abstract and ambiguous emotional representation was often hard to interpret and understand (e.g., (Yu et al., 2017)). Technologies that exposed user's stressful emotional representation prompted deliberation on what is the right amount of stress to trigger a healthy emotion regulatory process (Lobel et al., 2016). Another challenge noted in Huang et al. (2015) was the use of a set of discrete categories to map an emotional state. Participants complained that the 16 emotions they were directed to choose from to represent an emotional state "were not sufficient to express their emotional experience" (Huang, Tang, and Wang, 2015).

4.6.2. *Moments of Reflection*

Reflection refers to the process of stepping back from an experience, thinking, and evaluating it (Boud, Keogh, and Walker, 2013). The review revealed that researchers were challenged to provide emotional representation that both engaged users during the interaction with the technology and encouraged users to reflect upon their emotional state and emotional regulatory skills. Kolb (2014) emphasized the crucial role of reflection in the formation of abstract concepts related to social-emotional learning. He added that moments of reflection enable users to understand both the conscious and the unconscious components (Kolb, 2014). Deep understanding of the components can enable users to transfer and maintain the emotional learning skills throughout different contexts and times. However, most technologies were designed to create an engaging experience by drawing the user's attention to a certain task or activity that represented a behavior or physiological state that is associated with ER. For example, Zafar et al. (2017) presented a respiration-based biofeedback game that created a "more engaging alternative to traditional stress therapies" (Zafar, Ahmed, and

Table 2
Challenges themes

High-level theme	Design challenges
From Emotional Data to Emotional Representation - Providing appropriate emotional feedback	- Providing appropriate emotional feedback - Mapping an emotional state - Lack of context of emotional data
Moments of Reflection	- Awareness vs. attention - Enable transfer and maintenance - Interaction flow
Ethical Issues	- Raise self-judgment - Ensure privacy

Gutierrez-Osuna, 2017). While they created an engaging experience, they did not provide opportunities for the user to actively reflect upon the emotional experience and the self-regulatory skills that were applied. Moments of reflection are hard to design since they often harm the flow of the interaction with the technological intervention. Slovák et al. (2016) described the challenge of designing moments that encourage users to "stop & learn" from emotional experiences (Slovák et al., 2016).

4.6.3. Ethical Issues

The review indicated that there are ethical issues when designing interactive technologies for ER training. Leveraging social support has the potential to be beneficial for ER training with some technologies providing opportunities to share emotional data. However, sharing digital emotional data raises privacy ethical issues. Díaz-Escudero et al. (2018) presented a smartwatch that sensed the heart rate of children with ASD. The physiological data from children's everyday activity was sent to the caregiver's smart-phone (Díaz-Escudero et al., 2018). While this ethical concern is always relevant when storing personal data on digital devices, it is especially relevant when emotional data is stored and shared. Another ethical issue is the potential negative impacts of emotional representation. Niksirat et al. (2019) discussed the importance of using forms of emotion representation that avoided raising a user's self-judgement about their experience or their inability to regulate their emotions (Niksirat et al., 2019). Technologies that provided cumulative feedback often framed an emotional experience or an ER skill as 'good' or 'bad' (e.g., (Crepaldi et al., 2017)). These can raise user's self-judgment and result in unintended negative consequences on mental health. While the focus of the current review was not exclusively on the ethical perspective of technologies for ER training, we refer researchers and designers to a recent publication by Burr et al. (2020) that conducted a thematic analysis of the ethical issues concerning digital technologies for well-being (Burr, Taddeo, and Floridi, 2020).

5. Design Considerations for Future Interactive Technologies for ER Training

In addition to the themes presented and discussed above, which might be useful as descriptive tools for researchers, we now synthesize our findings and present a set of sensitizing concepts that emerged from the research to date. Given the early stage of most research in this field we pose questions related to each concept which may be worth exploring to move the field forward. We derived these questions based on our interpretation of the themes raised in the review, combined with key design features cited across multiple papers. Our motivation is to make these emerging concepts in the field accessible for researchers and designers during the iterative process of designing interactive technologies for ER training. Where relevant, we highlight under-explored areas for researchers and designers to study further. In cases of unresolved theoretical, conceptual and design challenges we provide pointers for other disciplines that can inform the design of future technologies in the field.

5.1. Theoretical Space

In our analysis we identified four theoretical models of behavior change that were used in previous technologies for ER training: Biofeedback and Neurofeedback, Psychological Therapeutic Models, Static Target Cuing, and Using Movement to Regulate Emotions. Each theoretical model can be used to lead to different (but not distinct) design features. We do not claim that researchers and designers should choose from the theoretical models that were raised in our analysis, but rather consider the opportunities offered by each theoretical model. We emphasize the importance of recognizing in early stages of the design process how theoretical models work, what their chain of reasoning is, and how they can be categorized within existing theoretical frameworks. We encourage researchers and designers to consider the following questions:

- *What is the chain of reasoning on how the technological intervention will lead to ER training?*
- *What are the intended outcomes of the technological intervention and how do they relate to the chain of reasoning?*
- *Can the technological intervention leverage opportunities from multiple theoretical models?*

In our findings, we present theoretical model themes that were used in previous publications. Here, we synthesize the theoretical model themes in light of the opportunities and challenges that were raised in the findings of the review. We emphasize an under-explored opportunity for designing technologies that are informed by more than one theoretical model, within a single technological intervention. In a mixed-subject experimental design with 24 participants, Knox et al. (2011) provided users with CBT psychoeducational content coupled with opportunities for biofeedback-assisted relaxation training. This approach enabled children to understand cognitively the process of how stress arises and how relaxation behaviors can prevent stress-based on psychological models of CBT, followed by experiential learning where children executed the previously learned relaxation skills during game-based biofeedback sessions (Knox et al., 2011). For a broader perspective on the importance of providing opportunities for reflection along experiential learning, see (Kolb, 2014). Another example for a technology that leveraged opportunities from more than one theoretical model was proposed by Paredes et al. (2014). They raised the tendency of previous technologies to design 'the best intervention' based on a single theoretical model. To contradict this approach they developed a smart-phone application that provided behavioral suggestions based on a machine-learning recommender system. The behavioral suggestions were chosen from diverse psychological theoretical models such as positive-psychology, CBT, and meta-cognitive. Each behavioral suggestion was provided based on the user's personal traits and contextual data. Through a 4-week field mixed-subject experimental design with 20 participants, findings indicated higher self-awareness of stress and lower depression-related symptoms measured by a Patient Health Questionnaire-9 (Paredes et al., 2014). For review of the potential of ML in providing more personalized therapy for mental health that is informed by multiple theoretical models and perspectives see (Shatte, Hutchinson, and Teague, 2019).

5.2. Level of Contextual Embeddedness

The results of the review indicate that 66% of the technologies were designed based on prevalent devices (see Section 4.2.1) and 55% of the technologies were designed for everyday context (see Section 4.2.2). Accordingly, 30% of the studies were conducted in field settings (see Section 4.1). With the growing development of mobile devices such as mobile phones and tablets, wearables, and tangibles we expect there will be a growing need to embed future technologies for ER training in the changing context of everyday activity. Providing access to 'in-the-moment' emotional support and opportunities for ER training during everyday activity and can enhance transfer and maintenance of ER skills throughout time and space. This raises the challenge of designing technologies that can fit various contexts within everyday activities. Technologies that were designed for ER training often required the user's attention when interacting with the technology, either by providing an emotion-based input (e.g., self-report (Fage et al., 2019)) or when receiving the emotional representation (e.g., behavioral suggestion (Carlier et al., 2019)). This type of interaction can disengage users from their environment. We encourage researchers and designers to consider the following questions:

- *Does the interaction with the technological intervention define the activity, or is it being embedded in other activities?*
- *Does the form of interaction fit the context of technology use?*
- *What is the interplay between the context of the activity and the interaction with the technological intervention?*

We highlight three approaches to embed technologies for ER training in everyday activity. In the findings section we describe various methods that were used to indicate users' emotional input (see Section 4.2.3) across various contexts (see Section 4.2.2). Some of these have been used to sense contextual data towards providing appropriate opportunities for ER training. This can be achieved by active data collection such as user's self-report (e.g., (Wang, Fischer, and Bry, 2019)), or by passive data collection such as location (e.g., (Huang, Tang, and Wang, 2015)) and activity by synching to the user's calendar (Kocielnik et al., 2013). For further review on the potential for passive sensing data to provide personalized psychological care in low-resource settings see (Byanjankar et al., 2020). The second approach is based on the plethora of possibilities for providing emotional representations (see Section 4.5.3). Building on such opportunities, researchers and designers can provide two parallel interactions with the technological intervention - one that requires the user's full attention and engagement when interacting with the technology and another where the user is not actively engaged with the technology. In an observation field study with 10 parent-child pairs, Pina et al. (2014) designed a mobile app that provided parents of children with ADHD in-situ behavioral support. The app was designed to support parents in two contexts. In times when the parent was fully engaged with the app, s/he received written behavioral strategies on how to navigate moments of duress, together with an appropriate glanceable display. In times when parents were not engaged with the app, during 'hot moments' with the child, a peripheral glanceable display that was previously associated with the behavioral suggestion was presented (Pina et al., 2014). For further review of the potential of just-in-time multistage technological interventions towards behavioral change, see (Choi et al., 2019). The third approach builds on the under-explored opportunities for providing abstract and ambiguous emotional representation. This speculative approach involves inviting users to interact with the technological intervention, rather than forcing an interaction. Sanches et al. (2019) designed a skin-conductance biofeedback system that provided an emotional representation that was abstract and ambiguous. This emotional representation invited users to reflect upon their emotional experience rather than 'being forced' to interact. An invitation to such 'meaning-making' interaction and designing features that are evocative and mysterious rather than didactic and explicit may potentially enable the user to decide when to interact with the technological intervention, in times that fit the context (Sanches et al., 2019). For broader perspective, we refer to Hallnas and Redstrom's concept of slow technology, a design agenda for technology aimed at reflection (Hallnäs and Redström, 2001).

5.3. Users Varying Needs for Intervention

Users vary in their ability to regulate emotions and their need for support by interactive technologies. The findings of the review show that previous technologies were designed to support a wide range of users in terms of age and health condition related to challenges with ER (see Figure 8).We emphasize the opportunity to create technologies that can be personalized to meet the changing needs of users (see Section 4.5.4). Applying user-centered design methodologies raises the possibility for the technologies to meet the expectations of the users and increase the ease in which the technology can be further used (Dabbs et al., 2009). As such, we encourage researchers and designers to follow a user-centered design process where end-users and/or stakeholders influence need identification and constraints of a certain design space. For example, Fage et al., (2019) interviewed families of children with ASD, teachers, school counsellors and psychotherapists before designing their technological intervention. This design approach enabled identifying users' requirements, usage scenarios, and design principles of an ER app for school inclusion of children with ASD (Fage et al., 2019). Another study followed a user-centered design approach in later stages of the design process. Miri et al. (2020) showed that when providing users the opportunity, they had different preferences of vibrotactile feedback for ER. Ignoring these preferences could negatively influence effectiveness of the interventions (Miri et al., 2020). For further review of methods to engage users in user-centered design methodologies, see Ole et al., (2017) which emphasizes a participatory design approach for giving users, specifically children, a voice in design. They elaborate on how users can be empowered to shape technological development and reflect on its role in their everyday use (Iversen, Smith, and Dindler, 2017).

- *Who are the target users of the intervention?*
- *What is the emotion regulatory challenge for these users?*
- *How do users currently overcome these challenges?*

The findings from the literature review (see Figure 8) show that most technologies designed for children were designed for non-healthy children. In contrast, most technologies designed for adult were designed for healthy adults. We highlight the gap in technologies that are designed for healthy children and non-healthy adults. Preventative interventions for healthy children in the context of ER have the opportunity to develop protective factors against different pathologies. The gap in technologies for ER training for adults with pathologies may be explained by the methodological challenge of running a research study involving such populations.

5.4. Emotion-based Input

The review identifies several methods for sensing an emotional experience (see Section 4.2.3). When interactive technologies for ER training are being implemented in a lab setting they have the potential to differentiate between emotional states under a controlled environment, i.e., attention vs. lack of attention (e.g., (Antle et al., 2019)) and stress vs. relaxation (e.g., (Lobel et al., 2016)). As of today, even in a lab setting, the ability of technologies to infer an emotional experience through a single input is limited. However, with recent technological development of mobile platforms (see Section 4.5.1), technologies claim to infer an emotional experience outside the lab context, 'in the wild' (see Section 4.2.2). The assumptions and capabilities of sensing technologies in the lab context, in a controlled setting, are fundamentally different outside the lab context as the nature of an emotional experience 'in the wild' is ambiguous, dynamic and complex. We encourage researchers and designers to ask themselves the following questions:

- *What does the data tell us about the emotional experience?*
- *What is the level of determinism of the input? Does the input sense data that can differentiate between different emotional states, or infer an emotional experience?*
- *Does the data consider contextual and situational factors that can influence the emotional experience?*

When designing technologies for ER training, we highlight the opportunity to explore in future research ways to improve data accuracy by using more than one source of data that can contextualize the data. These can be identified by wearable platforms that measure physiological signs in addition to mobile apps that gather contextual information such as location, activity, and users' self-report (see Section 4.2.3). Such opportunity can overcome some of the challenges raised in providing appropriate emotional representation (see Section 4.6.1). While coupling various forms of data can shed light on the nature of an emotional experience, multiple inputs can create a heavy-handed experience that might harm the flow of the interaction. Researchers and designers should strive to find the balance between designing technologies that can *determine* upon an emotional experience by using various sensing methods, and designing technologies that are less deterministic - technologies that encourage users to make sense of their emotional experience. For further review, see Howell et al. (2018) which raised the concern that emotional bio-sensing technologies "flatten the messiness" and that technologies tend not to acknowledge the "complexity of affect, feeling and emotion" (Howell et al., 2018).

5.5. Emotional Representation

The findings of the scoping review show a range of approaches to provide emotional representation (see Section 4.5.3). However, there are still challenges in terms of providing emotional representation that encourages moments of reflection (see Section 4.6.2). We encourage researchers and designers to consider the following questions:

- *Is the emotional representation in line with the level of determination that is provided by the input?*
- *Is the emotional representation designed to encourage users to interact with the technological intervention?*
- *Does the emotional representation encourage users to reflect upon their emotional experience?*

We raise the opportunity for future research to consider the level of determinism that can be provided from the emotion-based input and match it to the level of openness of the emotional representation. When using emotion-based input that can only *infer* an emotional experience (e.g., using a single input), we encourage researchers and designers to consider providing an emotional representation that is ambiguous and open-ended. This type of emotional representation can invite users to make meaning out of their emotional experience (e.g., (Niksirat et al., 2019)). However, without concrete guidance and support there is no promise that users will self-reflect upon their emotional experience. Reflection upon an emotional experience is crucial for learning and implementing ER skills. Even when technologies were designed to provide an open-ended and ambient emotional representation, users tended to "give more credit to the system than to themselves in terms of knowing how they were feeling in the moment" (Snyder et al., 2015). In addition, we highlight the challenge of designing experiences that encourage users to 'stop & reflect' (Slovák et al., 2016). In this context, there is an under-explored opportunity for designing technologies that encourage and facilitate social-emotional communication between users (Slovák et al., 2016), and technologies that raise social-awareness to the emotional state of users (Snyder et al., 2015).

Other technological interventions were designed to encourage users to practice ER training while playing video games and during meditation sessions. In these cases, there is an opportunity to create an experience that is engaging, towards extending the duration of the ER training and lowering the threshold for ER training. This can be achieved by providing multi-modal feedback (e.g., (Prpa et al., 2018)), an appealing narrative for a video game (e.g., (Khong et al., 2014)), or in the form of concrete representations where certain behaviors and mental efforts are rewarded (e.g., (Antle et al., 2019)).

5.6. Design Opportunity: Multistage Intervention for ER Training

Taking the opportunities and challenges raised in the review and the considerations mentioned in the sensitizing concepts and design considerations (above) and the different processes and strategies proposed in Gross's ER model (Gross and Muñoz, 1995) (see Section 2.1), one approach that we propose that might warrant investigation is to consider a multi-stage intervention for interactive technologies for ER training. We propose a few directions that might be beneficial to explore:

- Inform users on the physiological and cognitive processes that are associated with emotional experiences and provide users with concrete evidence-based strategies for ER. Provide users an option to select preferred ER strategies that can be applied later.
- When there is an indication of an emotional 'hot moment', provide users with a subtle feedback that raises the user's awareness of the need to perform the previous selected ER strategy. Design such feedback in a way that does not disengage the user from his/her everyday activity and can be ignored if the user is not interested in performing the ER.
- Provide users with a post-activity reflection piece. Such pieces can be provided through a screen-based platform that encourages the user to reflect on what worked or what did not work during the emotional experience. This piece can be delivered through concrete text, or through abstract and amorphous feedback that invites the user to reflect in an open-ended way.
- Enable users to personalize the core aspects of the technological intervention: what are the theoretical models that the ER strategy is based on (e.g., CBT and mindfulness); what are the inputs that are used to indicate an emotional 'hot moment' and when are they being measured (e.g., certain times of day, while standing in traffic during rush hours, when the user meets a certain person, when the user's heart-rate increases); what is the feedback that is provided to raise users awareness to the need of practicing ER strategies (e.g., vibration through a smartwatch, a sound played from the smartphone); and how is the post-activity piece delivered and when (e.g., a text message, an abstract visual on the phone).

6. Discussion

This paper makes two main contributions. First, we intend to guide researchers and designers interested in technologies for ER training to understand the field quickly and find relevant previous work, in order to better position their future work within the field. Second, based on where the field is to date, we speculate about topics that appear worthy of consideration, identify where current research exists and where more is needed, and identify gaps in research areas that might present opportunities. In line with the speculative nature of our findings we present the key considerations in the form of questions. Rather than providing answers to our questions, our goal is to encourage researchers and designers to ponder these questions during their research and/or design processes. To conclude, in addition to the design considerations mentioned above, we provide two research directions that are currently under-explored by the HCI community and provide gateways to relevant HCI research and non-HCI disciplines.

6.1. Supporting Moments of Reflection

Traditional methods for ER training are based on didactic learning approaches of skills 'that can be applied later' (Slovák et al., 2018). While didactic strategies can be effective, learning to regulate emotions needs to be taught and trained as an experiential process, during repeated 'hot moments' when the learner is overwhelmed with emotions.We note that previous work highlighted the opportunities of creating 'real-but-not-too-real' experiences, an experience that 'feels real' as a way to provide moments of experiential learning (Slovák, Frauenberger, and Fitzpatrick, 2017). In our review we noted that previous technologies often leveraged everyday emotional moments (e.g., (Paratore, 2020)), or alternatively created such moments (e.g., (Mandryk et al., 2013)) and transformed the once invisible processes that are associated with emotional experiences to be interactable and more visible. Experiences that are coupled with visible interactable elements provide opportunities for creating an experiential training of ER skills. However, even coupling didactic learning approaches and experiential training is often not enough. Reflection upon experiences is a key factor in understanding the conscious and unconscious processes of any learning experience, and specifically abstract concepts related to social-emotional learning (Kolb, 2014). According to a systematic review on Kolb's model of experiential learning, critical reflection which is defined as the act of meaning making has been found to act as a mediator in the different stages of the process of an experiential cycle (Morris, 2020). The process of actively reflecting upon ER experiences is often not supported in the technologies we reviewed. Technologies that did aim to provide moments of reflection did so by providing users with an open-ended emotional representation. However, we note that providing such emotional representations cannot be a 'stand-alone' design feature aimed at generating an active reflection process. A previous 8-week semi-technological intervention by Knox et al. (2011) did couple experiential learning and moments of active reflection. The experiential aspect was facilitated by a biofeedback system and a separate reflection piece was facilitated by a non-technological, in-class activity. The intervention was shown to reduce self-reported anxiety and depression measured by the Multidimensional Anxiety Scale for Children, State–Trait Anxiety Inventory for Children and the Children's Depression Inventory (Knox et al., 2011).

While there are previous technologies that can inform on promising directions in the context of ER training, the challenge of coupling a moment of reflection within experiential learning goes beyond the context of HCI. From the school of thought of Jean Piaget, Edith Ackerman coined in 1996 the phrases 'diving in' and 'stepping out' to illustrate the importance of differentiating between the process of learning through direct interaction with the environment (experiential learning) and forming the knowledge acquired from such interactions (reflection), towards developing knowledge (Ackermann, 1996). Within the HCI literature, technologies for supporting the process of reflection have been gaining much attention in the past few years. For example, the work of Fleck and Fitzpatrick (2010) synthesized different levels of reflection and illustrated how each level can be supported by digital technologies (Fleck and Fitzpatrick, 2010). Another review paper by Slovak and Fru (2017) called for researchers and designers to explore ways of designing technologies that scaffold reflection rather than providing data that is assumed to trigger reflection. To that end, they developed a conceptual framework in the context of SEL that offers a set of questions aimed to help understand characteristics of the 'right sort of' experiences that are likely to trigger reflection (Slovák, Frauenberger, and Fitzpatrick, 2017).

Both reviews (Fleck and Fitzpatrick, 2010, Slovák, Frauenberger, and Fitzpatrick, 2017) can provide a theoretical starting point for researchers and designers interested in designing moments of reflection in the context of ER training. However, there are still many open questions to be answered when designing interactive technologies that couple experiential learning and moments of reflection in the context of ER training, such as *When to offer opportunities for reflection on moments of ER training (e.g., right after the experience vs. at the end of the day?* and *What is the appropriate level of explicitness when inviting to reflect upon moments of ER training (e.g., concrete invitation through text vs. an amorphous visual feedback?*

6.2. Leverage Social Interaction

It has been well studied that interpersonal communication and social relationships have a significant influence on the process of learning, maintaining, and understanding an emotional experience (Rimé, 2009). For a broader perspective on the importance of social interaction on the mediation of ER processes, see (Coan, 2011). While technological interventions provide unique and various opportunities to create training experiences of ER skills, up to this day technology cannot replace the rich, emotional, and subtle nuances of making sense, communicating and reflecting upon an emotional experience with another person. Few technologies in this review were designed to leverage social awareness and support after an emotional experience (see Section 4.5.5). As most technologies that were analyzed in this review were designed for single users, researchers and designers interested in leveraging social interaction around of ER training might find guidance from other areas in HCI. Below, we provide gateways for researchers and designers to review studies that were motivated to leverage social interaction outside the context of ER training. We contextualize their recommendations in light of technological interventions that were analyzed in the current review and illustrate how other areas in HCI can inform the design of technologies for social ER training.

Based on an extensive literature review, Olsson et al. (2020) provided an overview of technologies that enhanced social interaction and mapped such technologies into three main roles: facilitation (e.g., supporting sense of community), invitation (e.g., increasing awareness), and encouragement (e.g., encouraging people to interact) (Olsson et al., 2020). For each role they mapped a social design objective and a design approach to reach such goals. For facilitating social interactions, researchers and designers should design technologies that disclose information about others (similar to (Huang, Tang, and Wang, 2015)) and provide topic suggestions (similar to (Slovák et al., 2016)). For inviting social interactions, researchers and designers should design technologies that encourage self-expression (similar to (Semertzidis et al., 2020)). Lastly, for encouraging social interactions, researchers and designers should design technologies that open space for shared activity (similar to (Slovák et al., 2016)).

Another review paper in the context of social interaction focused on certain technological platforms. Dagan et al. (2019) provided a design framework for social wearables through a survey of over 50 wearable devices that were designed to enhance in-person interactions (Dagan et al., 2019). They synthesized two areas of value for social wearables: augmenting existing social signaling and intervening in the social situation proactively. Augmenting existing social signaling refers to the information that can be expressed through computation regarding the wearer's needs, motivations, and preferences. Intervening in the social situation proactively refers to computation that creates clear and actionable calls for interaction (Dagan et al., 2019). In the context of ER training, augmenting existing social signaling can signal ways to interact in ways that fit the emotional state of the wearer through light, sound, and movements (similar to (Snyder et al., 2015)). Intervening in the social situation proactively can encourage the wearer and his/her surrounding to engage in ER-related activities (similar to (Pina et al., 2014)).

While both reviews are not related to ER training, they can serve as a baseline for introducing the various possibilities and considerations for creating social interactions around ER training (Dagan et al., 2019, Olsson et al., 2020). There are still many open questions to be answered when designing interactive technologies for social interaction around ER training, such as *What type of social interaction is intended in the context of ER? Is the emotional representation visible by the environment? What is the level of explicitness of the emotional representation? Is there symmetry between the users?*

7. Limitations and Future Work

Future work should continue to explore the quickly growing field of interactive technologies for ER training. The design considerations generated in this paper were based on an inductive process of analyzing previous HCI papers about interactive technologies used for ER. We acknowledge that a different set of papers, analysis method, and coders could have resulted in different theoretical models. In addition, based on the relatively early developmental stage of the field, indicated by the research quality of the papers included in the analysis, the findings of the opportunities, challenges, and design considerations are largely speculative at this moment. This paper presents a first attempt to describe the current state and provide design considerations for designing interactive technologies for ER training. In the context of interactive technologies for ER training there are still many technical challenges, especially in terms of sensing data that can better inform on an emotional state. However, we believe that even with great advancement of sensing technologies the challenge of providing an appropriate emotional representation that will be beneficial for ER training will still exist. As such, the focus of this paper is not to solve technical challenges but rather provide relevant theoretical knowledge, synthesize design considerations and provide gateways to other disciplines that can inform the main usability challenges in the context of designing technologies for ER training.

8. Conclusion

In this paper, we review interactive technologies for ER training based on 65 peer-reviewed publications. With new opportunities created by recent technological development, our review shows that there has been a solid base of early-stage work in designing, implementing, and sometimes envisioning futuristic human-technology interaction around ER training. The scoping literature review provides a snapshot of the field while highlighting different approaches for designing such technologies, their theoretical model, their target users, opportunities where they appear to provide unique benefits, and challenges where design guidance is ambiguous or underspecified. We speculate on design considerations that may help researchers and designers better position their work in the field and provide pointers for other disciplines that can inform current research gaps in the field. We conclude by emphasizing two research directions that may warrant further exploration in the context of technologies for ER training: technologies that couple experiential training and moments of reflection upon ER skills and technologies that leverage social interaction to promote social-emotional-communication upon ER skills.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Paper Analysis

https://docs.google.com/spreadsheets/d/1ZAR3BMvBpu-Ytknsnl nYU2suCzjMRHOTCt6Qyo-VKuM/edit?usp=sharing

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