Mental health care in a pandemic: A survey from a design and interaction perspective

B.Sc. Final Thesis
Iñigo Artolozaga de Ariño
Supervisor: Kristin Neidlinger
University of Twente
i.artolozagadearino@student.utwente.nl

ABSTRACT

The COVID-19 virus pandemic has swiftly impacted our way of life. Traumatic experiences like becoming ill, losing a loved one, losing a job or becoming socially isolated are more frequent than ever before. Numerous studies indicate that the toll on mental health generated by these phenomena cannot be handled by the current public mental health care infrastructure. The aim of this paper is to find ways to rethink the current digital mental health care infrastructure via user-centered design in order to adapt to this sudden, unforeseeable spike in mental health care demand. The research is split in two parts: First, a literature review will shed light on the current state of affairs of digital mental health care methods and report on emerging technologies that show promise in the digital mental health care world. The second one is a survey in which individuals especially at risk of developing common mental disorders during a pandemic will share their thoughts about interaction with these technologies. This research aims to establish a first point of contact between novel, scalable mental health digital solutions and individuals affected by the pandemic.

Keywords

Digital Mental Health Care, Pandemic, Human-Computer Interaction

1 Introduction

1.1 Context

Due to the outburst of the novel COVID-19 respiratory virus, the world's social, cultural and economic landscape has shifted. Due to governments restricting movement in many countries, even in some cases preventing citizens from leaving their houses without a justifiable reason, the world during this time has become less physically connected and more digitally connected [48]. Some individuals who are in the demographically at-risk groups or have preexisting health conditions have had to completely isolate themselves to stay safe. Frontline health workers are working overtime under poor conditions, high risk of contagion and sometimes even ostracism by their communities due to the risk they present [27, 24]. The impact that these circumstances has on mental health cannot be overstated [53, 34, 24].

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Despite the overwhelming medical response in this pandemic, there has been a noticeable level of neglect towards mental health care [29, 21] that could socially develop into a more pessimistic outlook on life and cause an even worse economic recession afterwards [34]. Despite current implementations that try to give a digital approach to mental health care (even trying to gamify it in some cases [8]), it would not be trivial to look carefully into how to approach offering massive mental health aid to citizens in this time of need [19]. A possible, future-proof solution could be found in the digital and mobile realms [25, 31].

1.2 Research Questions

This work will attempt to answer two big research questions, which will both be divided into more concise and manageable subquestions:

- RQ1: What design and interaction choices are pertinent to provide mental health care for the largest amount of people during a pandemic?
  - SQ1: Does the interaction need to be different for frontline healthcare workers, virus patients and socially isolated people?
  - SQ2: With limited physical resources, how can the best user experience for everyone, irregardless of their condition, be ensured?
- RQ2: How can the wave of digital pervasiveness be ridden to ensure the well-being of mentally at-risk people during a pandemic?
  - SQ3: What recent advancements in mobile technology would enable us to most effectively and reliably reach the most people?
  - SQ4: To what extent would 'gamifying' mental health help users stay constant in their treatment?

All in all, the objective of this research paper is to gain a better understanding of the role that software and its interaction with users had regarding their mental health in a pandemic, and what could be improved in future emergency situations like it. Despite this paper being set in the frame of a pandemic, this research holds scientific value, not just for possible future pandemics or other situations of extreme isolation, but also for the short-term future, in which software will become more and more present in our daily lives and in healthcare system [23].

1.3 Related Work

Considerable research has been conducted in the field of Mobile Health (or mHealth). This field combines healthcare with the ubiquitous technological revolution, and touches upon subjects such as Affective Computing, Biometrics, Psychology and Human-Media Interaction. Seeing as it is a relatively new sector,

enabled by the surge of computing power and mobile connectivity [41], there are few works in this field that can be traced back longer than a decade. The European Health Commission urged the scientific community to expand on this field, with the intention of it supporting the delivery of higher quality healthcare by enabling more accurate diagnosis and treatment [11]. This paper was a catalyst for many others in this topic, ranging from foundational papers such as the one from Steinhubl, which "provided the foundation to radically transform the practice and reach of medical research and care" [41], to journals that documented incrementally innovative works in the field as years went by and technology advanced, such as Silva [37] or Kao [9].
Mental health in a pandemic is a novel topic. As a matter of fact, the existing literature on the topic has been evolving as research has progressed, which has enabled adaptation to new insights. Van Agteren uses online data from mental resources from before and after the pandemic, and concludes that the pandemic sample showed worse scores on depression, stress, anxiety, well-being, life satisfaction, and resilience measurements [46]. An editorial in the Journal of Medical Internet Research Mental Health by Torous explores the success of digital mental health care during the present crisis and how technologies like apps will soon play a larger role in the healthcare infrastructure [43]. He calls for additional investment, high-quality data and workforce training in the topic. These works are important as foundational pandemic relief works, but are just calls to action, which will be responded to within this literature investigation and the following social research.
D'Alfonso discusses the design mantras that should be respected in the field of Persuasive Technology, which encompasses all technology that is designed to change attitudes and behaviors through social persuasion and influence [13]. The conclusions of this paper, which ask for the regulation and decommercialization of digital mental health care, are also important and should be taken into consideration while designing tools to fit this use case. It is urgent to reimagine this field's paradigm, adapt quickly to the current circumstances to mitigate damages and work towards the ubiquitousness, accessibility and effectiveness of these systems to provide services to as many people as possible.

2 Methodology and Approach

In order to find answers to SQ2 and SQ3, literature review was done. For this, the six steps to build a literature review as defined in the book "The Literature Review: Six Steps to Success" [26] were used, which in a summarized manner include selecting a topic, developing the tools for argumentation, searching the literature, surveying the literature, critiquing the literature and, finally, writing the report.
To find answers for SQ1 and SQ4, a survey was conducted. Subjects at risk of declining mental health due to their circumstances inside the pandemic [53] were asked about their opinion on the novel topics identified during the literature review. With the information gathered in the literature research, three groups were defined to conduct the research on: COVID-19 patients, Healthcare Workers and Socially Isolated Individuals. The selected survey sample population was chosen under the assumption that people that fall inside these groups would be available at any point in time to respond to a relatively short online survey, and alternative strategies were devised in case this number was not reached, although this was not the case.

Since this research falls into the category of Human-Media Interaction and Persuasive Technology in general, it will be conducted using the guidelines established by BJ Fogg, one of the fathers of the latter discipline, in his foundational article entitled *"Persuasive computers: perspectives and research directions"* [16], which are:

1. *Identification of artifacts and techniques:* Identifying persuasive technologies and how they work on the user. This will be achieved with the literature review and the report.
2. *Analysis of effectiveness and effects:* Assessing the effectiveness and the unintended effects of the technologies. These will be found with the survey.
3. *Disclosure of findings:* Regardless of the results, the research must be divulged. This will be done in the Results section.
4. *Call to action:* If any result is deemed to be have a social or ethical significance, the research must advocate for change in these topics. This will be covered in the Future Prospects section.

3 Literature Review and Report

3.1 Methods

3.1.1 Initial Topic Selection

The literature review and subsequent report would be divided in several topics. The first step of the literature review was identifying the topics to look into further. After delving deep into multiple journals related to the topic at hand, several topics inside the field of Affective Computing were identified and it was considered important to conduct a deeper investigation on them. They were the following:

- Chatbots
- Mobile Biometrics and Biofeedback
- Gamification of Content

These are all technologies which aim to improve mobile implementations by increasing their effectiveness and accuracy. However, each use different channels and techniques to achieve these.

3.1.2 Procedure and Inclusion Criteria

Inspecting illustrious journals in the areas of interest (like the Taylor and Francis Human-Computer Interaction Journal, IEEE's Transactions on Affective Computing and the Journal of Medical Internet Research Mental Health journal), a total of (n = 132) articles were indexed in the initial search stage(See Appendix, section 9.1). These mostly consisted on reports outlining the state of the art on these three topics, with an emphasis on either Healthcare as a whole or more focused on Mental Health implementations. These papers had an average of 43 references each. Pruning was conducted, focused on getting rid of redundancies, shared references and content not relevant to the topics at hand. The remaining articles were filtered to only include papers that were peer-reviewed and from the past 10 years. The end result was (n = 84) redundancy-free works which were further surveyed, and the in order to elaborate the report.

3.2 Chatbots

3.2.1 Introduction

Over the last decade, the technology industry has seen a spike in interest towards smart conversational interfaces (mostly known as chatbots). They consist of machine agents that serve as natural language user interfaces for data or service providers [3]. These are seen by many tech giants (like Uber, Microsoft and Facebook [12]) as the future in the way in which users interact with webs, apps and also devices. As a matter of fact, over the last years all of the big four tech hardware companies in the United States release voice-powered digital assistants (Apple's

Siri , Google's Assistant, Amazon's Alexa and Microsoft's Cortana), all of which have been deployed in all of their respective product ranges [12].
Chatbots can be traced back to ELIZA (1966), a primitive conversational agent that tried to mimic the responses to messages typed in by people in the way a psychotherapist would [3]. Eliza was able to fool some users into thinking that they were actually talking to a human, and the principles used in its development laid a foundation for the structures of chatbots, such as specific phrases, keywords and preprogramming responses [52, 14]. Another notable examples of paradigm-shifting chatbots are PARRY (early 1970s), which imitated a person with paranoid schizophrenia [10]. When psychotherapists were asked to speak to the bot, less than half were able to differentiate between it and a real paranoid person [14]. ALICE (1995) was an enhanced version of the then 30-year old ELIZA. As opposed to its older relative, ALICE compartmentalized the chatbot engine and the language knowledge model, which allowed the latter to be swapped for other models when desired. This, in combination with ALICE being open-source, allowed for a boom in progress in this field [1].

3.2.2 Chatbots in Healthcare

Despite the scarcity of human resources in these times, especially in the healthcare sector, it is important to keep a good contact and relationship with patients to optimize the outcome of their treatment [15, 30]. However, it is equally as important to keep patients from going to hospitals if it's not strictly necessary, to prevent overcrowded and saturated environments. This necessity is even greater in a pandemic because of the risk of infection. It would be a good solution, in terms of hygiene but also of scalability, to have systems online in which people can check the severity of their symptoms to see if they should seek further medical attention. Still, while doing this, it should not be necessary to sacrifice the human touch that some people consider important when dealing with delicate topics such as their health. Chatbots are a good way to achieve this.
Weiss hypothesizes that "an embodied agent (as opposed to a simple interface) can improve user satisfaction and engagement with a computer system, and in some cases can even improve users' opinion of the objects being described by the system" [51]. There is a consensus that the present objective of modern healthcare chatbots is to help patients get the attention (both medical and interpersonal) they need without using up all the expensive human resources (doctors and other healthcare staff). The ideal solution is a system which is capable of replicating the user experience in a human-human interaction with the increased convenience of being able to be accessed from one's home. They can help the patient get information they need and follow them through their treatment, among other things. Fitzpatrick points out that they can provide access to both the practical and emotional aspects of care when human health providers are not available [15].

3.2.3 Chatbots in Mental Health Care

Statistics indicate that there is much more demand of mental health treatment than there is offered, and projections indicate that the gap between these two is increasing every year [25]. Historically, professionals in the mental health field have relied on face-to-face consultations with their patients, in clinic settings which are away from their normal lives [18]. There is potential to implement mobile ubiquitousness in the world of therapy. It would allow therapists, through mobile apps, to keep track of any patient's mood, behavior and unusual activities. Chatbots are starting to gain traction as a means for therapists to keep track of their patients without the need for physical meetings.
The field of chatbots in mental health is still not as developed as others [30]. As ELIZA attempted and many medical chatbots have tried to improve in the last half century, chatbots in this field should strive to provide its users with an experience as close to a human-human conversation as possible. The use case of most existing mental health care chatbots doesn't deviate from what that established earlier about health chatbots as a whole: They are mostly tools that make human knowledge accessible in an easier and more accessible way.
Cameron develops a sketch chatbot with the objective of providing users with a more accessible and interactive journey to access a library full of self-help resources. This repository contains categories such as anxiety, depression, obesity and misuse of drugs. The demo chatbot is created to provide a more interactive way of leading the user into the PDF worksheets, and leading them to areas in which the user wants to receive information [6]. According to the author, however, the approach used in this implementation to display information fails to be engaging and interactive for the user, which could be a deterrent for some users.
In contrast to this, in 2017 a company called WoeBot released a chatbot which employs Cognitive Behavioral Therapy (the most evidence based and widely used therapeutic approach). Its main channel of service is a mobile app. The company conducted a study to prove the effectiveness of their service, with satisfactory results [15], with subjects pointing out the appeal of the engaging experience of using the chatbot as accessing text resources traditionally.

3.3 Biometrics and Biofeedback

Mobile devices are becoming more and more present as tools in the healthcare world. In the present, these devices come equipped with a wide array of powerful sensors that aid on the diagnosis, tracking and treatment of a variety of health conditions, including mental health related ones [54]. It seems like external biometric devices will soon be a thing of the past. While using data from built-in sensors like the heart rate scanner found in some present phones is a possible approach for the tracking of physical symptoms[40], the treatment of mental health conditions requires more complex approaches to this subject [54].

3.3.1 Mobile Context Sensing

Since last decade, mobile phone technology started enabling what is known as 'mobile context sensing'. Burns discusses a mobile application that constantly inputs data from 38 different mobile sensors from people that suffer from depression in a machine learning model that decides whether or not they are in immediate danger. The sensors used to build the virtual context range from hardware-sourced ones like perceived ambient light and physical location, to software-sourced ones like call records and unread messages. If, when inputted with a certain data from the sensors, the model decides that the person is in danger, medical services are immediately alerted [5].
Singh and Long conducted a study in which participants first had to take a standardized mental health measure test, and after they had to have their mobile phone metadata and sensor information fed into a machine learning algorithm. Comparing the estimations from the automated model and the initial tests revealed an accuracy of around 80%. Their objectives were paving the way for cheaper, automated mental health assessments with timely escalations when required [38].
Wahle, building upon a smaller-scoped study from a year earlier [36], employed similar context sensing concepts, albeit in a more proactive manner than in previous studies. The proposed app would scan for a certain set of environmental parameters using the aforementioned array of sensors and administered context-inspired interventions based on Cognitive Behavioral Therapy in a 'just-in-time' manner. Although the study that tries to gauge the effectiveness of this system is not randomized and

there is no control group, it sheds some light on the possibility that these methods will streamline and improve the experience of the user when being treated, by using unobstructive methods of remote health monitoring [49].

It is important to make a note about the aforementioned 'just-in-time' adaptive intervention design. In the context of design and interaction, Nahum defines this practice as "an intervention design that adapts the provision of support (e.g., the type, timing, intensity) over time to an individual's changing status and context" [33]. Singh and Long's work [38] also strives towards an implementation like this. Spruijt adds to this definition by pointing out that the aim of this implementation is to "deliver support at the moment and in the context that the person needs it most and is most likely to be receptive" [39]. This system could be applied in two different ways to systems in this scenario: To administer reminders of interaction with the application, and to get the user emergency help, both only when the user needs them and is receptive of them. These two events should have two different environmental and contextual triggers [32].

3.3.2 Issues

There have been numerous critiques on this concept, which mainly center around the difficulty of developing a model with data from multiple different sources [35], the ethical and privacy issues of continuous context sensing [17, 50] and the severe increase in battery consumption that constant sensor data reading entails [2]. Rahmati analyzes the state of the art for context sensing solutions and points out that most are addressing these problems by limiting the number of inputs in the case of the source problem and limiting the frequency of sensor sampling in the case of the battery problem [35]. However, advances in data encryption technologies and legislation, as well as in power efficiency of sensors, are making this pitfalls less of a problem over time.

3.4 Gamification of Content

3.4.1 Introduction

Torous conducted a study in which mental health care patients receiving treatment in both private and public institutions were asked to provide a list of the apps they had installed in their phone. Mental health applications represented the sixth most popular category of apps in their phones. The author concludes with ideas about looking at the more popular mobile app categories with the goal of implementing some of their tried and tested formulas into mental health apps in order to increase their appeal [44].

A trend that has seen considerable growth as developers start to notice the commercial success of mobile games is the 'gamification' of content for mobile applications. This concept consists in adding gameful mechanics, more traditionally found in videogames, to applications that are unrelated with this sector in order to increase the value for the user and increase their engagement with the service [20]. It is difficult to define precisely what these mechanics and techniques are because there is no consensus between papers on this, but a large majority agree that avatars, leaderboards, levels, digital rewards, tangible prizes, competitions and social pressure can be considered gameful elements [7].

In 2019, Taylor et al. performed a Randomized Controlled Trial which wanted to prove the efficacy that the gamification of a simple digital diary would have on retaining interest in its usage among young adults. The results showed that, when compared to a physical diary and a simple digital diary implementation, the game-motivated version (which offered in-game rewards for every successful entry) did a better job at keeping users motivated to continue using the service [42].

3.4.2 Gamification of Mental Health

Delving deeper into the mental health field, Brown et al. analyze the user adherence in 82 different implementations of gamification in mental health digital programs. Compared to a control group of non-gamified systems, these gamified implementations tend to retain adherence much better in long programs, but doesn't make a big difference in shorter programs [4]. Some implementations already address the problem of adherence in long programs [45], but more research needs to be conducted on the topic of gamification in order to make a difference regardless of the program length.

Zhang explores the effect that gamification has on the treatment of attentive biases, which can develop into more severe mental health issues and whose traditional treatment is usually highly repetitive. The study was inconclusive in finding a relationship between gamification of the treatment and higher effectiveness, but it raised the question of whether gamification lost effectiveness after the effect caused by its novelty wore off. To try to solve this, Tsay et al. addressed several critiques to the present gamification systems and tried to solve them by implementing more continuity throughout long term tasks, with positive results [45].

3.4.3 Issues

Versteeg outlines the ethical issues related to gamification. He points out that the persuasive role of gamification poses ethical questions for designers, and that the tools that gamification employs can be used manipulatively and impact user values like privacy and autonomy, leading in extreme cases to addiction to the reward systems [47]. Kim suggests that, whereas gamification is not inherently exploitative or harmful for users, a framework for the evaluation of potential ethical issues must be designed and used by designers to take precautions in this regard [22]. Despite this, Marczewski points out that ambiguity on the definition of gamification will be used for developers to get away with unethical practices. He believes that the currently existing 'codes of ethics' don't go far enough, and that gamification becomes unethical when the designer exploits the user's psychology to manipulate them into doing something that is not in their best interest [28].

3.5 Conclusions of Review and Report

These three concepts have developed over the last years and show promise when it comes to enhancing the user experience in mental health software. More research remains to be done in these areas in order to reliably reach a wide audience. A basic sketch of a system which implements all the technologies studied in this review can be found in the Appendix (Section 9.6).

Regarding chatbots, substantial progress has been achieved since their inception in the 1960s. They appear to be a good option for a potential emergency mental health care digital deployment. The personal connection that chatbots pursue and try to emulate would not only be beneficial to improve the user experience, but to provide at-risk individuals with the social stimuli that the pandemic has deprived them of. Although there are advanced implementations already (like the aforementioned WoeBot), more work needs to be done trying to bridge the gap between face-to-face therapy and chatbot-powered therapy, both in the implementation of evidence-based therapy techniques and in methods to make the user feel the personal connection that human therapy offers.

Regarding the topic of context sensing, the discussed implementations show promising results in predicting the user's behavior from sensor data and aiding them when they most need it. Seeing as it is in early stages of development and deployment both as part lifestyle applications and in healthcare ones, an effort

must be done to implement this concept in a secure manner, in order to avoid its privacy concerns.
The gamification of content has been a popular subject for applications that do not belong to the world of games, with hopes of increasing their overall appeal but also the user adherence to the provided service. More research in the area of videogame reward techniques sneeds to be transferred over to mental health apps and tested for user feedback. Additionally, more research needs to be conducted on gauging the effectiveness of certain methods to see of they really make a difference in the engagement of the public.

4 Survey

As mentioned in the planning of the paper, the next step after identifying the most promising concepts in mobile mental health was to provide a first point of contact between the users and these novel concepts. To achieve this, an online questionnaire was designed, which is described below.

4.1 Methods

Seeing as the circumstances that the pandemic have created on users are unprecedented, a primary, cross-sectional study was considered optimal to capture their needs in this particular point in time. The channel of choice was a web-based survey. This would ensure that people could get reached regardless of their physical location and health status, without violating social distancing recommendations. This social research was ethically approved upon review by University of Twente's Ethical Commitee.

4.1.1 Inclusion Criteria

As indicated above, three groups were identified that, according to numerous psychiatry journals [34, 19] are the most at risk of showing symptoms of common mental health complications. These sections were Healthcare Workers, COVID-19 Patients and Socially Isolated Individuals. The set objective was to have at least 20 people from each of these groups of interest.

4.1.2 Recruitment

In order to keep the sample as demographically diverse as possible, various channels were used to recruit participants for the survey. The two main participant sources were personal contacts that belonged to either group and additionally participants from medical forums. Like with every web-based survey, there were concerns with the legitimacy of the responses, so to ensure that the legitimacy of the survey was not compromised some measures were taken. For the first source, only trusted personal contacts who would respond truthfully and accurately were selected. For the posts in the medical forums, a brief introduction to the research was introduced online and afterwards subjects had to get into contact if they were interested in participating. The effort involved in personally contacting the researcher was deemed enough to keep people with ill intent away from the study.

4.1.3 Data Collection and Analysis

For the survey, an online survey service was used. The survey period lasted one week, and afterwards it was closed, not allowing more responses. Before the start of the official survey, some pilot runs were had, in which a small but diverse group of people went through the survey and gave feedback about the content and also the structure of the survey.
Simple and cross tabulation was performed with the resulting data, which outputted the basic results of the survey but also allowed for some question's results to be filtered and sorted based on the results of another. This provided additional insight on how certain circumstances affected the opinion of the participants on the proposed technologies. Incomplete answers were discarded.

4.1.4 Survey Structure

At the start of the survey, some calibration questions are asked in order to determine what group of interest participants fell in. Afterwards, some questions about participants' mental health and digital experiences were asked in order to attain data to perform comparisons afterwards (see Appendix). The main section of the survey, however, came last. In this final section, the participants were presented with the three technologies featured in the literature review and the survey asked for their opinion on them. In order to get a more diverse and justified opinion from the participants about the investigated technologies, their feedback was divided into three different sections, asking the following questions to participants:

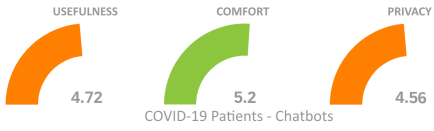
- Usefulness: Would using this technology benefit you in any way? Would you use it willingly and frequently?
- Comfort: Would you have difficulties using this? Would you get used to using this technology quickly?
- Privacy: Would you be feel safe using this privacy wise?

For each of these items, the participants were asked to provide a score from 0 to 10 regarding the three different technologies presented to them. Additionally, they could optionally provide more information on how exactly that specific technology could have helped them cope with their mental health situation during the pandemic.

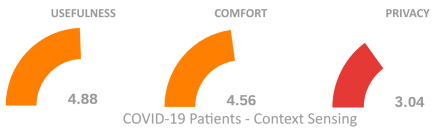
4.2 Results

A total of 312 individuals participated in the survey and went into the initial classification procedures. From this group, a total of 250 participants fell into one of the three designed interest groups and completed the survey (25 COVID-19 patients, 53 Healthcare Workers and 172 Socially Isolated individuals).
In the following sections, the displayed graphs show the participants' views and opinions on the three aforementioned technologies. Where a full semicircle would represent a perfect score (10/10) the colored portion represents the actual score. In the Appendix (Sections 9.3 to 9.5), more detailed results can be found. Additionally, for every section the scores will be cross tabulated with the questions about their digital experience during the pandemic. These additional questions can be found in the Appendix (Section 9.2).

4.2.1 COVID-19 Patients

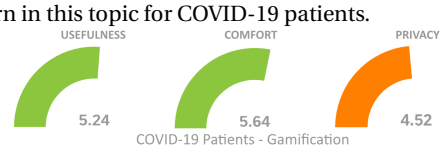


The results indicate that the interest in chatbots by COVID-19 patients is low. There are some positive testimonies agree that chatbots would be useful for patients to *"talk to something, share [their] difficulties"*, but most people in this category agree that *"[they] don't want to talk to robots, they are intelligent but do not have emotions"* or that *"it would feel weird talking to a machine"*.



Their feedback for Context Sensing (CS), as pictured, is not positive. Although some people say that this could help *"Calming [them] down when [they] need it the most"*, most patients agree

that *"it would amplify [their] anxiety"*. For people that said that they had lost healthy habits in the pandemic, Usefulness and Comfort were 13% and 10% better graded, respectively, than those who did not lose such habits. Additionally, privacy is a big concern in this topic for COVID-19 patients.



Feedback on gamification is more positive than with the rest for COVID-19 patients. Participants claim that *"It would distract [them] from the topic in a good way"* and that it would *"It would definitely challenge and motivate me"*. People that used mental health apps in the quarantine gave this concept a 20% and 27% higher score in Usefulness and Comfort, respectively, than those who did not.

4.2.2 Healthcare Workers

Healthcare Workers give slightly better scores to chatbots on Usefulness and than COVID-19 patients, but their perceived levels of privacy are much worse than that of the latter. Testimonies say that it would help this group by *"making [them] feel less lonely"* or *"using them to vent"*. Some even look into the inner-workings of the system and say that *"it would help [them] get to information that [they] need faster"*.

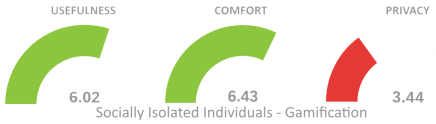
Judging by the data, they are not attracted to the concept of Context Sensing at all. Testimonies range from a simple *"I don't like the idea at all"* to a more constructive *"For someone that would need this, it seems like a good concept. But it is not for me."* People who claimed they lost healthy daily habits in the additional questions gave this concept a passing grade both in Usefulness and Comfort, but there were not enough people in this group to make a dent on the overwhelming negative majority.

Finally, Healthcare Workers did not like the concept of gamification as much as the other groups, as it can be seen in the numbers. Some positive testimonies include that it would help them *"disconnect from work and have a bit of fun"* and *"gain gratification from achievements"*. A great number, however, say that *"[they] prefer to be with family"*. People who lost healthy habits during the pandemic reported 23% and 21% higher scores on Usefulness and Comfort, respectively, that those who did not.

4.2.3 Socially Isolated Individuals

It seems like Socially Isolated individuals have a better opinion on chatbots when it comes to perceived Usefulness compared to the other two groups, but the difference is minimal. This group is also concerned about the implications of this technology on their privacy. Although some people say that *"[they] would prefer humans"*, most acknowledge that this was not a choice for them and say that this concept would have made for *"someone to talk to 'in person'"* and that it "would help [them] exteriorize [their] problems".

Surprisingly, they give Context Sensing a slightly higher grade than the other groups both in perceived Usefulness and Comfort. Some participant testimonies claim that it would *"avoid stress and anxiety by notifying [them], make [them] more aware of unhealthy habits"* and even think of examples such as *"It would interrupt stress when I'm spending much time reading about the virus"*.



Their response for Gamification is the best response to any technology by any group. Testimonies say that this would "hold [them] accountable to self care" and "get [them] addicted to taking care of myself", which aligns well with the intended purpose of the concept itself. There is still an important concern with privacy, even in this seemingly less intrusive technology.

4.3 Discussion

4.3.1 Summary of Findings

There does not seem to be a considerable difference in the interest of different groups for the three proposed technologies. However, it must be taken into consideration that these numbers represent the combined opinion of all the participants, even if they did not feel the need for mental health care during the pandemic or even felt like they lost healthy habits during the lockdown. It is interesting to take a closer look at how the people that admitted that they could have benefited from these services responded to the survey in a more isolated manner. For example, there is a considerable difference in the opinion of COVID-19 patients, depending on if they claim they have used mental health apps during the pandemic or not. This difference translates into up to a 20% higher grades in perceived Usefulness and Comfort in some technologies. This difference carries over to the other user groups in a lesser magnitude.

When cross-referencing the privacy worries about the different presented technologies with the degree of experience participants have with mental health applications, the results point out that people with previous usage of these applications are 20 to 30% less worried about their privacy. Judging by the testimonies given by part added as an addendum by some participants after rating the proposed concepts, it seems that there still remains a combination of stigmas around mental health and Human-Computer Interaction in a healthcare context, which keeps people away from these implementations. More demographically focused research remains to be conducted in order to gauge if this is a generationally prevalent phenomenon.

In terms of the gamification of content, the results appear to be quite positive. Apart from being the best valued concept in the three rating categories out of the three proposed ones, more promising data can be found if the pool of participants is further filtered. For people who claimed to see a decline in their mental health during the pandemic, the average rating for gamification's Usefulness is 6.03 out of 10. For people who lost healthy habits during the lockdown, the average score is 6.39. Perhaps the most promising statistic, however, is that the average score by people that did not make use of a mental health

application during the pandemic but acknowledge they could have benefited from using one is of 7.18 out of 10.

4.3.2 Implications

Throughout the cross-section of all the assessed groups, opinions of chatbots, mobile context sensing and gamification of content seem to be convergent. While it appears that the pandemic has affected all these groups' mental health in a similar way, ranging from the loss of healthy habits to social isolation, both in varying degrees, it must not be forgotten that these groups are demographically and contextually heterogeneous. These results do not mean that everyone has suffered in the same way and would have preferred the same technologies to aid them in this process, it means that the distinction created by the circumstances of the pandemic does not seem to represent an actual rift in opinions. Further research needs to be conducted toward a successful segmentation of the affected population in a pandemic. Seeing as the solution to traditional scalability problems seems to lie within software, another interesting segmentation that could be explored in the future is population age and technological savviness, and how that affects their experience and design preferences.

5 Conclusions

The findings from the literature review and the survey suggest that progress is being made in the implementation of digital systems in the existing mental health care infrastructure. Additionally, the design needs and preferences of these three aggrupations generated by the circumstances of the COVID-19 pandemic do not differ substantially from each other. While the experiences of the individuals have been different during the pandemic, it seems that, when classified this way, they exhibit similar opinions about Chatbots, Mobile Context Sensing and Gamification in the frame of mental health care. It can be concluded that the chosen classification heuristic is not effective in the segmentation of design desires in the population when it comes to mental health care in a pandemic.

5.1 Subquestions

Regarding Subquestion 1, according from the data recovered from the survey participants belonging to the three specified groups, everything indicates that there is not a significant difference in the design and interaction preferences between them.

Regarding Subquestion 2, the findings of the literature review suggest that the scalability of software is unrivaled in the physical world. However, the limitations of the papers surveyed indicate that there are design opportunities for bridging the gap between the digital and physical experiences when it comes to mental health care.

Regarding Subquestion 3, while from the analysis of the state of the art in mobile mental health solutions can extract that there is already a great number of software which provides an experience increasingly similar or even better than the one physical treatment would, it seems like more work needs to be done on increasing the user experience and the overall appeal of these experiences. Moreover, from the survey results and testimonies it can be extracted that there still remains a "digital resistance", especially prevalent among healthcare workers, which makes people reluctant to transfer traditionally physical practices to the digital world.

Regarding Subquestion 4, as mentioned in the Discussion section of the survey, the gamification of mental health mobile content not only would improve the user experience and help retain user engagement but it also seems to increase the appeal that these implementations have on individuals with no experience in these kinds of services.

5.2 Future Prospects

In the case that a pandemic happens again in the near future, the world will be much better equipped and prepared medically for it after learning from the COVID-19 pandemic. This should also be the case for mental health care. More steps have to be taken towards a hybrid (digital/physical) mental health care infrastructure that can handle the demand generated by generally traumatic experiences such as a pandemic. More action needs to be taken to ensure these needs are met.
Riding the wave of open source software, it would be interesting to develop modular, free to use and modify chatbots similar to the ALICE framework [1] and allow everyone to train, refine and improve the official models.
Research about Mobile Context Sensing shows promise in monitoring and helping patients at the exact point they need it. Research in this field should focus both on increasing the accuracy of the models employed to anticipate behavior and on designing secure sensor data processing systems to prevent privacy issues. It seems that this last issue remains as one of the biggest concerns for the population regarding digital healthcare. Although the gathered data shows that this concern is substantially lower for people who have experience using digital health services, it remains a challenge which must be solved with software transparency and 'secure-by-design' software.
Gamification appears to be a highly promising concept in the field of mobile mental health. As previously mentioned, the appeal and adherence it generates on users translates into an overall better user experience. However, while the appeal is clear, more research remains to be conducted on how to more effectively bring concepts from videogames to mental health applications, as well as how to properly and proactively tackle the potential ethical issues that arise from its use.
Software, as the findings of this paper indicate, can work effectively as a first layer of contact between mental health care and potential patients. A good implementation of a hybrid infrastructure would use this digital resources to avoid overwhelming the existing physical infrastructure by redirecting the most at-risk patients to more empirically proven physical therapy, while administering automated help to lower-risk individuals. Nevertheless, the quality gap between a physical and a digital approach will decrease with more research in digital mental health care.

6 Limitations

Regarding the literature review, the fact that the topic that is covered in this paper is so novel means that the research conducted in it is limited. Even though the the number of studies and papers about the pandemic grew more and more each week as they were published, the available literature at the beginning of the investigation was scarce. Nevertheless, the sections of the paper pertaining to the virus were gradually modified in every iteration of the work, to incorporate new available information.

Regarding the survey, the classification of participants was done by separations that stem from the circumstances of the pandemic. In retrospective, as it is mentioned in the paper, this survey could have benefitted from another layer of classification, preferably demographic, to add more nuance to the findings about the design preferences of the population during the pandemic.

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9 Appendix

9.1 Literature Review - Distribution of initially indexed papers

	Healthcare	Mental Health
Chatbots	30	17
Biometrics	19	24
Gamification	20	22

9.2 Additional questions (by group)

	Virus Patients	Healthcare Workers	Socially Isolated
Has your mental health declined during the pandemic?	23 (62)	48 (72)	85 (44)
Did you reach out for help during the pandemic?	13(59)	8 (17)	21 (25)
Do you think you lost healthy habits during the pandemic?	21 (58)	30 (46)	100 (53)
Did you use mental health apps during the pandemic?	9 (25)	13 (20)	27 (14)
Could you have benefitted from a mental health app? (Only asked to people with no MH app experience)	13 (50)	26 (50)	77 (48)

Table 1: In each cell, the first number represents the number of people who responded "Yes" to the corresponding question. The number in parentheses represents the percentage that the first number respresents over the total amount of respondents.

9.3 COVID-19 Patients - Feedback of technologies

	Usefulness	Comfort	Privacy
Chatbots	4.94 (2.88)	5.09 (2.99)	4.75 (3.23)
CS	4.83 (2.60)	4.83 (3.00)	2.70 (3.23)
Gamification	5.38 (2.88)	5.69 (3.13)	4.41 (3.51)

Table 2: Mean (First number) and Standard Deviation (Number in parentheses)

9.4 Healthcare Workers - Feedback of technologies

	Usefulness	Comfort	Privacy
Chatbots	4.85 (2.76)	5.16 (2.73)	2.89 (2.75)
CS	3.96 (2.80)	4.19 (2.96)	2.52 (2.94)
Gamification	4.83 (2.96)	5.60 (2.90)	3.64 (3.08)

Table 3: Mean (First number) and Standard Deviation (Number in parentheses)

9.5 Socially Isolated Individuals - Feedback of technologies

	Usefulness	Comfort	Privacy
Chatbots	5.08 (2.78)	5.23 (2.83)	2.71 (2.73)
CS	5.50 (3.06)	5.13 (3.07)	2.23 (2.64)
Gamification	6.02 (2.93)	6.43 (2.82)	3.44 (3.03)

Table 4: Mean (First number) and Standard Deviation (Number in parentheses)

9.6 Diagram of Proposed System