**A Framework for Recruiting into a Remote Measurement Technologies (RMTs) study: Experiences
from a major depressive disorder cohort**

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On behalf of the RADAR-CNS Consortium**Abstract**

The use of remote measurement technologies (RMTs) across mobile health (mHealth) studies is becoming increasingly popular, given their potential for high-frequency symptom monitoring outside of routine clinical appointments. However, many RMT studies fail to report on engagement and recruitment statistics, with the few who do citing a wide range of recruitment rates. There is a need for the standardisation of best practices for successful recruitment into RMT research, critical for both research validity and reproducibility. The current paper aims to create a framework for successful recruitment into RMT studies, reflecting on the experience of RADAR-MDD, a large-scale, multi-site prospective cohort study utilising RMT to explore the clinical course of people with major depressive disorder across the UK, Netherlands, and Spain. More specifically, the paper assesses four key strategies for successful recruitment, alongside a review of the common barriers to participation and how to avoid them. Finally, the strategies and barriers outlined are combined into a single model of recruitment, that can be used as a framework to inform future study design and evaluation. Such a model will be applicable to a variety of stakeholders using RMT in healthcare research and practice.

Background

The use of mobile technology in healthcare (mobile health; mHealth) has the potential to revolutionise both clinical practice and research (Liao et al., 2019). Novel remote measurement technologies (RMTs), for example smartphone applications, sensors and wearable technologies, are a subsection of mHealth, and can enable frequent, longitudinal and personalised health monitoring. Currently, the assessment, and subsequent treatment, of many chronic health conditions is often limited to retrospective recall during routine clinic visits, which can be biased by cognitive and memory heuristics (Nahum et al., 2017). RMT data offers the potential for high-frequency symptom monitoring, which is more reflective of an individual's daily experience (Jones & Johnston, 2011).

RMT data holds particular relevance for conditions of a recurrent nature. Major depressive disorder (MDD) is a mental disorder characterised by persistent low mood or anhedonia, often fluctuating between periods of remission and recurrence. Prevalence of MDD worldwide increased 18.4% from 2005-2015 (Geneva: World Health Organization, 2017). The economic burden of MDD is currently estimated at \$326 billion (2020 values), exacerbated further by an increased risk of comorbidities and healthcare resource utilisation experience by those with high relapse and recurrence rates (Gauthier et al., 2019; Greenberg et al., 2021). Data obtained through a combination of smartphone questionnaires (active RMT; aRMT) and inbuilt sensors (passive RMT; pRMT) from phones and wearables can provide rich, multi-parametric information on symptom change, risk factors, cognition, sleep and diurnal patterns of behaviour, sociability and physical activity. Crucially, the integration of RMTs into MDD research could provide the temporal resolution needed to detect indicators of future depressive episodes (Naslund et al., 2015).

For the potential of RMTs to be achieved, it is important to understand whether and how people engage with research studies of this nature. Engagement is a multi-stage construct indicating the extent to which a resource is actively used (O'Brien & Toms, 2008). Initial 'point of engagement' in this instance relates to an individual agreeing to participate in an RMT study. Whilst findings suggest that people living with MDD endorse the view that RMTs could be used to detect and predict relapses (Polhemus et al., 2020; Simblett et al., 2019), work has highlighted key barriers to recruitment into such research. These include user-related factors, such as personal agency and privacy concerns, as well as system-related factors, including usability (Bauer et al., 2018; Simblett et al., 2019). In practice, RMT studies often currently present small sample sizes (Simblett et al., 2018). Recruitment rates into mental health trials range between 0-75% (Liu et al., 2018); reduced help-seeking and motivational behaviours are often cited as reasons for low engagement with research in depression (Brown et al., 2019; Sherdell et al., 2012). Low recruitment rates present several limitations, including an increased

risk of selection bias, a loss of statistical power and reduced generalisability, hindering the ability to produce valid results worthy of implementation into clinical practice (Teague et al., 2018). Despite calls for adherence to Strengthening the Reporting of Observational studies in Epidemiology (STROBE; Vandenberg et al., 2007) guidelines, a large majority of RMT studies do not report on recruitment statistics as part of engagement measures (Simblett et al., 2018), thus little is currently known about recruitment into RMT research.

The need to understand recruitment into remote measurement studies has increased exponentially since the COVID-19 pandemic. Isolation and social distancing have forced both clinical research and practice to halt face-to-face appointments. Healthcare services are rapidly seeking innovative ways to monitor health remotely, not least for contact tracing of COVID-19 symptoms, but also for continued measurement of pre-existing conditions outside of the clinic (Behar et al., 2020). Recruitment into studies of smartphone apps designed for tracking COVID-19 symptoms shows initial promise, reflecting a national effort to combat the pandemic (Drew et al., 2020; Menni et al., 2020). However, understanding engagement with these technologies against the backdrop of the digital divide and digital exclusion has never been more imperative in ensuring healthcare equity (Watts, 2020). A fundamental challenge in healthcare will be coordinating a sustained response beyond these times, during which adoption of, and engagement with, remote (mental) health tracking has been noted as of great importance (Holmes et al., 2020; Moreno et al., 2020; Owens et al., 2020).

Currently, a framework of best practice for recruiting into longitudinal RMT studies does not exist. In the wider mHealth literature, an emerging trend for papers sharing recruitment experiences has encouraged standardisation and evaluation in the field (Watson et al., 2018). Strategies such as digital advertising, research registry recruitment, provision of researcher contact details and making iterative changes to app content have all been cited as factors which aided in recruitment into mHealth intervention trials, spanning common mental health conditions (Lattie et al., 2018), cardiovascular health (Pfammatter et al., 2017) and risky health behaviours (Watson et al., 2018). More specific to RMT use, Druce et al. (2019) reviewed successful recruitment into two aRMT apps for symptom tracking in rheumatoid arthritis between 30 days and 12 months. However, there is currently no clear consensus as to whether these findings can be applied to studies that utilise a combination of aRMT and pRMT to track depression over longitudinal periods, given the potential for additional participant burden. Efforts to translate this body of work into the field of multi-parametric RMT research could provide the necessary first steps in understanding how best to recruit into such studies, and in doing so, produce high quality results across academia and beyond.

The RADAR-MDD study

The Remote Assessment of Disease and Relapse- Major Depressive Disorder (RADAR-MDD) study is a large-scale, multi-site prospective cohort study that aims to transform MDD patient care using multi-parametric RMT (as part of the wider RADAR-Central Nervous System (CNS) public-private partnership study: <https://www.radar-cns.org/>). Android smartphone apps and a wearable fitness device (Fitbit Charge) are used to track MDD symptoms longitudinally, with the aim to determine whether such data can provide information predictive of depressive relapse (see Matcham et al. (2019) for more information). Eligible participants met with the research team for a single enrolment session, before being followed up remotely for a minimum of six months, maximum of 3 years. The study aimed to recruit 600 participants across London (UK), Barcelona (Spain) and Amsterdam (The Netherlands). Recruitment began in November 2017 at the London site, acting as a year-long pilot for the recruitment and enrolment process before the remaining two sites joined in September 2018 and February 2019 respectively. By end of follow-up in June 2020, RADAR-MDD had exceeded its overall recruitment target ($N=623$), and in the London site alone had recruited 175% ($N=350$) of its target sample. It was also able to sustain a steady level of recruitment throughout the COVID-19 pandemic. Thus, the study provides an opportunity to increase the transparency of reporting participation rates and common barriers for non-participation in this field, as a multi-parametric RMT study with an extensive follow-up period.

The current paper aims to pave the way towards understanding initial participant engagement with multi-parametric RMT research. Using the RADAR-MDD project London site as a case study, it will present a framework of considerations for recruiting into RMT research, specifically those with depressive cohorts. The authors describe core areas to consider for maximising recruitment, each reflecting on specific examples from RADAR-MDD. They then explore some main obstacles to participating in the study, and some proposed solutions. This work provides a starting point for the evaluation of recruitment pathways in RMT research, alongside a framework for future work in the public or private sector to build upon.

Section One: Recruitment Strategies

Four main areas of consideration for recruiting into an RMT study are presented, reflecting on the experiences of the RADAR-MDD study. These key areas are: (1) the need for co-design with target

population, (2) a recruitment team fulfilling key competencies, (3) minimising participant burden via streamlined procedures and (4) making enrolment accessible for all while being open to iterative change.

1. Co-design with service-user involvement

A key element an RMT trial should consider is co-design with service users. User involvement is essential to ensure usability and interest in the technology and is especially relevant for studies that struggle with low uptake and adherence (Liu et al., 2018; Yardley et al., 2015). Users can reference personal lived experience when evaluating a system, and can provide valuable feedback on the design, procedures, communication materials, and implementation into clinical practice (Anderson et al., 2019; Bano & Zowghi, 2015).

RADAR-MDD included a work-package dedicated to Patient and Public Involvement (PPI). A series of work has been published, including systematic reviews and focus groups, with those with lived experience of MDD across three countries, exploring priorities for using RMTs to manage depression (Simblett et al., 2018, 2019). This work-package also facilitated a Patient Advisory Board (PAB; Matcham et al., 2019). The PAB had input from the initial design through to data analyses; service users participated in wearable device selection that culminated in using the Fitbit Charge device for data collection (Polhemus et al., 2020), reviewing of participant-facing documents and app usability testing. In addition to the PAB, the UK site also consulted two local service user advisory groups at King's College London regarding payment plans and providing feedback data.

This person-based approach has been widely recommended in interventional designs (Yardley et al., 2015); we suggest that it is equally important in observational research. In utilizing the expertise of the PAB, the RADAR-MDD study was designed for, and by, individuals with similar lived experiences to those being recruited. This created a smooth transition from protocol design to study execution.

2. The recruitment team

Through consultation with the PAB, and previous literature that cites human contact as a predictor of retention in longitudinal studies (Abshire et al., 2017; Teague et al., 2018), it became clear that a small patient-facing research team available to participants was essential. For the RADAR-MDD's London site, the team consisted of three full-time research assistants, who provided the promise of daily technological support and clinical risk assessments to participants. Here, future RMT studies should consider the necessary competencies and training this team will require.

2.1 Hiring the recruitment team

Firstly, when hiring a patient-facing team, an RMT study should acknowledge the competencies needed to match the complexity of study design, technology used, and likely support needed. In a systematic review of longitudinal clinical studies, eligible research team staff were screened for: specialist experience working with the target population, cultural competencies, communication skills, empathy and sensitivity (Abshire et al., 2017). For RMT studies specifically, we recommend that patience and awareness of potential technological barriers is integral, as much of the contact with participants during recruitment involves communicating with individuals of varying technological abilities.

The RADAR-MDD study London site screened for these competencies in behavioural interviews, consisting of a mock recruitment session with a colleague outside of the research team. The applicant was provided little information about the study in advance and asked to respond to questions from a mock participant. The aim of this activity was to assess situational judgement, and the ability to build social rapport, field participant questions, and create an atmosphere conducive to requesting further support if needed. This was based on work by Salgado and Moscoso (2002) indicating that conventional and behavioural interviews assess different constructs with the latter being more suited for this role.

During the recruitment period, it became clear that the team could benefit from additional staff to accommodate participant interest. To this end, a mental health nurse, based at the local NHS Foundation, was seconded to the team on a research placement for 12 months part-time. The benefits of this were three-fold: 1) increased capacity for recruitment calls and enrolment sessions, 2) provision of expert clinical advice for risk assessments, and 3) an attempt to accommodate participant queries on the use of RMTs in clinical practice.

2.2 Staff training

Secondly, it is vital for recruitment staff to be trained on how to introduce the study most appropriately to the target population. Courteous and clear communication is key here. Particularly, when recruiting for an RMT study that often feature complex designs and procedures for the participants. It is critical for staff to be able to discuss the study goals and procedures in a vernacular appropriate to the population, while following a standardised script. This should be a part of a larger training manual that can be provided to the researchers, standardising the process across sites. Mental

health cohorts may pose additional considerations, such as phone call anxiety, so the team should be confident in communicating procedures and diagnostic interviewing via various channels.

Furthermore, it is important for the research team to manage participant expectations by clearly explaining the participant burden and the aims of the study, particularly if the RMT is not used as an intervention but rather as a data collection tool alone. Similarly, it is imperative that research staff can answer potential questions regarding technological concerns, data protection, data security, and confidentiality, as these are key areas of participant concern in RMT studies. This is especially relevant for long-term RMT studies, as participants are signing up to engage with (often new) technologies that will become a new part of their daily routine. This can seem daunting, thus a research team that can provide information that might eradicate concerns, and that is easily contactable throughout participation is likely to promote confidence in enrolling. Thus, regardless of the potential of these technologies for remote data collection, the importance of human contact should always be considered here.

Finally, using RMT in research is relatively novel, so the promise of a personable, knowledgeable, and trained research team, both during recruitment and throughout the study, was paramount to the success of study recruitment.

3. Minimising participant burden

Another key element to consider when designing a longitudinal RMT study is that participants are being asked to share large amounts of personal data. Where RMT, and in particular pRMT, is by design often 'invisible', the addition of a wide range of exploratory aRMT variables might have caused individuals to feel overwhelmed by the amount of data that is being tracked, and the amount of time and energy it will cost to incorporate the technology into their life. Thus, studies should consider reducing participant burden as much as possible.

We reflect on two ways the RADAR-MDD study attempted to make the recruitment process as streamlined and rewarding as possible: (1) easy participant onboarding and (2) incentivisation for participation.

3.1 Streamlined onboarding: identify, contact, track

A study recruiting into RMT research should create a standardised pathway for researchers to guide participants from potential participation to enrolment date. This provides clarity for both the research team and participants.

The RADAR-MDD study created a system of statuses that helped identify, contact and track potential participant journeys to enrolment. The team used several methods to *identify* a pool of potentially eligible participants which included both team-initiated (Consent for Contact databases; C4C) and participant-initiated (form on the RADAR-CNS website) approaches. A central spreadsheet kept a log of contacts, whereby each individual was assigned a status from “needs contact” to “enrolled” (see Figure 1). This enabled the team to identify individuals quickly and progress them accordingly. Not only did this streamline the recruitment process, but it allowed for the easy creation of meaningful graphics to quantify the process to the extended team.

Figure 1. A process diagram of the various statuses from initial contact to enrolment.

3.2 Benefits of participation- incentivisation for outcomes

Another factor critical for RMT studies to consider, when wanting to offset participant burden, is incentivisation. The debate over financial incentives for participants is a long-standing balancing act for ethics committees and principal investigators, regarding the influence over study design (e.g., Parkinson et al., 2019; Phillips, 2011). Commonly, agreement is found that allows for financial incentives where the risk to the participant is negligible and can result in more robust research outcomes (Zutlevics, 2016).

When reflecting on the RADAR-MDD project, at the London site participants were paid £15 for the initial enrolment session and were reimbursed travel expenses. They were also informed that they would receive £5 for every 3-month outcome assessments they completed (long-form questionnaires sent via email) during the follow-up period. Financial incentives were not offered for aRMT questionnaires. This was based on feedback sessions with the RADAR-CNS PAB, the FAST-R group and research conducted by Mohr et al. (2011). Mohr et al. found that financial rewards can provide motivation for tasks that take more time, while these same rewards for engaging and quick

tasks can be perceived as controlling or indicators that the individual lacks motivation. Additionally, feedback sessions with the RADAR-CNS PAB and the FAST-R group were held identifying similar

In addition to monetary incentivisation, the offer of technology can be an intriguing prospect for potential participants. Here it was critical to provide equal opportunity and to address digital divide, as a substantial proportion of the population do not have access to smartphones and this group may be particularly relevant for mental health studies (Greer et al., 2019). Thus, the RADAR-MDD study provided all technology free of charge (a Fitbit Charge device and a compatible Android smartphone where not already owned). This was coupled with a technology user guide, and the offer of help with switching devices if required. As a result, owning or having experience with the technology was not a prerequisite for participation. This allowed for recruitment of a diverse range of participants, some of whom had never used a smartphone.

A third incentive for enrolment into RMT studies is moral alignment with the aims of the research, and the altruistic belief that engaging with such research will provide clinically valuable results (Anawar et al., 2017). During the RADAR-MDD recruitment process, participants were reminded at various points that the ultimate aims of the study were to implement findings into clinical practice. They were also informed that there would be the opportunity to view some aspects of their data, during participation (e.g., heart rate, step counts on the FitBit dashboard) and as an infographic at the end (e.g., mood fluctuations across time) (Matcham et al., 2019). As a result, potential participants were encouraged to feel they were contributing to a tangible, innovative way of using technology to manage health, which will hopefully prove beneficial to themselves and the wider MDD community.

Overall, combining a streamlined recruitment process with tailored incentives to combat barriers to engagement work together to reduce burden for participants, and should be considered essential for recruitment into RMT research.

4. Iterative process

Finally, when recruiting it is imperative to strike a delicate balance between protocol adherence for increased reliability, and the need for flexibility, for example in accommodating participant needs or incorporating feedback.

4.1 Flexibility in enrolment procedure

When designing enrolment procedures, RMT studies should be aware of the need to be flexible in response to differing levels of technological expertise and various personal circumstances (e.g., mental health affecting the ability to travel for enrolment). At the London site, RADAR-MDD

participants were offered a choice of three enrolment formats: (1) research centre visit for in-person session, (2) a home visit, or (3) a video call (and a separate procedure that was accessible to those with hearing impairments). During the in-person and home visit sessions, a member of the research team would introduce the study, remind the participant of the aims and set up the technology for them. Online sessions followed a similar procedure, but the participant set up the devices themselves once received in the post, following live instructions. These options of different enrolment procedures provided participants the flexibility to make study enrolment as effortless and comfortable as possible.

To standardise enrolment procedures, the research team created scripts and checklists for each method. However, it became apparent from early participant feedback that certain aspects of the session could be adapted further to promote engagement. For example, RADAR-MDD included experience sampling methodology (ESM; Myin-Germeys et al., 2018) for 6-day time periods throughout the study; where this was initially described in the study instructions as a 'questionnaire', initial confusion surrounding its high frequency led to researchers changing the description to 'diary task', to convey a more quick-fire questionnaire. Furthermore, early participants noted feeling uncomfortable wearing the Fitbit at night, leading researchers to advise to 'wear the device as much as you feel comfortable'. Incorporating early feedback into the recruitment and enrolment protocol served to enhance clarity, particularly as RMT research is relatively novel.

Thus, RMT studies should consider the different ways in which they can make the enrolment process both standardised and adaptive to environmental or personal circumstances that might make traditional study onboarding less feasible.

4.2 Recruiting remotely during the COVID-19 pandemic

As well as adapting to individuals, RMT study protocols should ideally be able to adapt to changing environmental circumstances. Though unprecedented, the COVID-19 pandemic provided a case study for one of the key benefits of working with RMTs: structures are likely in place to continue with data collection and recruitment, during times when face-to-face contact is not permitted.

The RADAR-MDD study was able to continue the onboarding process easily during the UK lockdown caused by the COVID-19 pandemic. In part, this is reflective of the decision to re-contact individuals who were previously unreachable. However, it is also reflective of the little adaptation needed to switch to fully remote onboarding procedures, given that this was already an established method of enrolment. Online recruitment procedures (explained previously) were followed as usual, with the team contacting individuals via work mobiles from home office. Technology delivery through postal networks was also unaffected.

Researchers conducting RMT studies should thus be open to adapting the recruitment procedure in response to circumstance, and importantly acknowledge and take advantage of the remote nature that these technologies afford.

Section Two: Obstacles to Participating

When presenting a framework for recruitment into RMT studies, it is also important to consider participant barriers to participation that hinder the ability to hit recruitment targets. In RADAR-MDD two key obstacles to recruitment were encountered: (1) technological barriers and (2) health-related barriers; Figure 2 shows the breakdown of reasons given for declining to participate in the study (n=161) and ineligibility (n=165). Here, we discuss these and consider how they can be minimized in future research.

Figure 2. A recruitment flowchart from initial contact to enrolment for the RADAR-MDD London site.

¹ Of total contacts, denominator=1104

² Of willing & assessed for eligibility, denominator=581

1. Technology-related barriers

When considering barriers to enrolment for the RADAR-MDD study, participants' unwillingness to switch to an Android device was the most common reason for participant ineligibility (46%). Here participants expressed having set up their homes/work on devices on alternative operating systems, e.g., iOS, making the switch impractical. Meanwhile, 22% declined the use of a

smartphone, or felt generally uncomfortable wearing a watch or jewellery on their wrists for long periods.

Future studies should consider these limitations and work to make their technology compatible with a wide variety of operating systems. Furthermore, it is important for future studies to acknowledge the potential biases that occur in the data because of these barriers. In RADAR-MDD study, despite the provision of technological support, the sample could be biased towards people who are already using smart-watches and smartphones. However, it is possible that this is reflective of the type of sample that would choose to use symptom tracking routinely should it be implemented in clinical practice. Thus, it is imperative for studies to consider the type of sample they are hoping to recruit and why.

2. Health-related barriers

Another obstacle faced in RADAR-MDD recruitment were health-related barriers. An unexpected finding here was the necessity to reflect on the potential health impact the technology may have on certain comorbidities. For example, the presence of comorbid eating disorder made some (3%) decline participation. This was not a factor the team considered prior to recruitment, yet it highlights the importance of understanding the triggers that viewing some aspects of personal health data, in particular in relation to physical activity, might cause. Here, the potential effects of symptom monitoring on those with a history of eating disorders might be detrimental and thus need consideration in future RMT studies.

Of the reasons given for declining participation in the study, low mood only accounted for 1%. This is particularly interesting as it suggests that presence of depression does not deter many individuals from participating in remote symptom tracking studies, and indeed 61% of participants did report a current depressive episode at baseline. Conversely, it could be argued that presence of low mood could prompt an interest in mood tracking, and thus an interest in participating.

Overall, future studies should consider health-related obstacles in their study design and consider: the negative impact the technology could have on individuals with certain comorbidities, and how current episodes of illness can impact participants' willingness or reluctance to participate in the research.

Discussion

This paper aimed to present a framework for recruitment into RMT research, using the RADAR-MDD London site, a longitudinal, multi-parametric RMT study, as a case study. Despite varying reports of initial engagement in the previous literature (Pratap et al., 2020; Simblett et al., 2018), in particular in MDD cohorts (Brown et al., 2019), the study successfully recruited 350 participants over 31 months from the London centre, exceeding a preliminary target of 200. Following a recent focus on recruitment ‘lessons learned’ literature from the wider mHealth field, this paper presents an attempt to mirror this framework in the rapidly expanding RMT space. Several strategies that aided recruitment into the RADAR-MDD study have been assessed. A review of the technology and health-related barriers to participating further boosted understanding of engagement with RMT research. As such, we present an initial model of recruitment into multi-parametric RMT studies (Figure 3).

Figure 3. A model of recruitment into RMT research studies, based on insights from the RADAR-MDD project London site. Arrow weight for recruitment barriers indicates prevalence of this barrier, as seen in the RADAR-MDD project.

This model outlines some foundational steps worth considering when recruiting participants for RMT research, based on knowledge gained from the RADAR-MDD project. As discussed, first successful recruitment should be preceded by thorough consultation with service users, and the acquisition of a suitably trained patient-facing team. Presence of contactable researchers has been found an indicator of retention in the mHealth literature (Abshire et al., 2017; Druce et al., 2019); we

argue that it is also a crucial facilitator to initial engagement with RMTs. The design of RMT studies should consider a core research team not as an optional extra, but rather a necessity to the successful onboarding of participants who might have concerns around the use of novel technologies.

Secondly, the process of contacting eligible participants should be streamlined where possible, providing suitable incentives during the recruitment/enrolment process and beyond. RADAR-MDD found a combination of C4C databases and online advertising an effective strategy for identifying potential participants.

Thirdly, potential barriers to participation should be anticipated beforehand and incorporated into the research design. These include, but are not limited to, a user experience that is compatible across operating systems, devices that are suitable for the less technologically-literate, and ability for personalisation depending on medical comorbidities. Where previous work suggested privacy and data security concerns as potential barriers to RMT uptake (Bauer et al., 2018; Simblett et al., 2019), this study found these factors were not noted as reasons for declining participation. It is possible that running the study from a renowned, academic institution partly alleviated apprehension here.

Finally, RMT studies should prepare to offer flexible enrolment procedures to suit individual needs and respond to early participant feedback. This includes taking advantage of the remote nature that RMTs afford for times when face-to-face sessions are not permitted or suitable (whilst maintaining a core research team presence).

Strengths and Limitations

This paper presents a model of recruitment into an RMT study based solely on a pilot case study from the London site of the RADAR-MDD study. It is important to acknowledge that where the fundamental recruitment and enrolment procedures remained largely similar across the remaining two sites in Barcelona and Amsterdam, several local and national processes impacted on the translation of this model. For example, staff recruitment protocols in Amsterdam meant that staff were hired from a rotating pool of research assistants, rather than exclusively for the RADAR-MDD project. In Barcelona, the core recruitment team comprised a post-doctoral researcher and a part-time research assistant, with an additional 40 clinicians and health professionals promoting recruitment into the study. Also, differing ethical procedures across the three different countries led to discrepancies in incentivisation and payments offered to participants. Therefore, application of this model cross-culturally should be taken with caution.

It should also be noted that the model outlined in this paper does not include strategies to combat biases within the recruited sample. Reviews of recruitment into remote mHealth studies have

found age, geographical and ethnical biases in samples (Pratap et al., 2020). The present study faced similar challenges. Aside from offering free technology to account for a possible digital exclusion in the target population, no targeted recruitment was conducted. Future work will focus on analysing participant demographics and provide more detail into potential biases in the sample.

A final limitation is the inability to analyse the demographics or technological abilities of those who refused participation. This would have allowed for a comparison with those who did participate, and an exploration of correlating factors. Further investigation might be possible for those recruited via C4C databases, for whom such data is retained. However, in the current study this would not be representative of the total participants contacted. Thus, future work building on this framework should consider collecting this data as it could provide valuable insight into the type of individuals inclined to participate in an RMT trial.

Notwithstanding these limitations, the RADAR-MDD study is an exemplar of over-recruitment into an RMT study of MDD. This adds weight to recent work that suggests that participants with MDD advocate the use of technology to manage their health (Polhemus et al., 2020; Simblett et al., 2019), and provides an encouraging foundation for future work.

Implications for Future Study

The proposed framework provides the basis for both the application of this model to future RMT studies, and the evaluation of other successful recruitment strategies in similar work. Thus, it is fundamental that future RMT studies build on this framework to share experiences, to ultimately provide for higher-quality trials with powered results to improve patient care. Going forward, future work should look to combine these findings with similar insights from longitudinal studies that have successfully recruited and retained MDD participants (from different cultures, communities, populations). Taken together, this body of work will be critical in understanding engagement in RMT research.

A valuable area of consideration for future work will also be the extent to which successful recruitment into RMT studies is offset by feasibility. The RADAR-MDD is part of the wider RADAR-CNS public-private partnership consortium, which involved a large amount of planning, resources, staff streamlining and funding before recruitment commenced. For the London site, this afforded three, full-time research assistants working solely on the project, which allowed for greater flexibility in enrolment sessions and increased time spent explaining the study to participants who might not have otherwise agreed to take part. Other projects might not have similar resources, appropriate patient-facing teams or access to service user advisory groups. Future work should seek to explore the trade-

offs and compromise between different aspects of the model, and their impacts on reaching recruitment targets.

In considering the COVID-19 climate, building upon the current work has never felt timelier. The RADAR-MDD study London site recruited between November 2017 and June 2020, and thus these results encapsulate both pre-pandemic and UK lockdown periods. While this framework will remain applicable to face-to-face research settings when permitted, continuing to recruit during the pandemic has given the opportunity to exemplify RMTs as a viable and acceptable way to remotely collect health data. The transition towards a greater reliance on technology, as precipitated by COVID-19, may also act as a further facilitator of future RMT recruitment. Work should investigate the impact that the pandemic has had on recruitment strategies in various fields, and any resulting trends in utilising RMT in research and practice.

Conclusion

The current paper outlined the four key pillars of a successful RMT recruitment strategy used in the RADAR-MDD project. These insights formed the basis of a framework model for consideration when recruiting into RMT research studies. Such reflections will assist future researchers and stakeholders with a vested interest in the field. They will also promote transparency and encourage others to build on this framework with their own knowledge, creating a more standardised, and successful, approach.

Conflict of Interest Statement

M.H. is principal investigator of the RADAR-CNS programme, a precompetitive public-private partnership funded by the Innovative Medicines Initiative and European Federation of Pharmaceutical Industries and Associations. The programme receives support from Janssen, Biogen, MSD, UCB and Lundbeck. D.C.M. has accepted honoraria and consulting fees from Apple, Inc., Otsuka Pharmaceuticals, Pear Therapeutics, and the One Mind Foundation, royalties from Oxford Press, and has an ownership interest in Adaptive Health, Inc. P.A. is employed by the pharmaceutical company H. Lundbeck A/S. All other authors declare that they have no competing interests. VN is an employee of Janssen Research & Development, LLC and hold company stocks/stock options.

Acknowledgements

The RADAR-CNS project has received funding from the Innovative Medicines Initiative 2 Joint Undertaking under grant agreement No 115902. This Joint Undertaking receives support from the European Union's Horizon 2020 research and innovation programme and EFPIA (www.imi.europa.eu). This communication reflects the views of the RADAR-CNS consortium and neither IMI nor the European Union and EFPIA are liable for any use that may be made of the information contained herein. The funding body have not been involved in the design of the study, the collection or analysis of data, or the interpretation of data.

This paper represents independent research part funded by the National Institute for Health Research (NIHR) Biomedical Research Centre at South London and Maudsley NHS Foundation Trust and King's College London. The views expressed are those of the authors and not necessarily those of the NHS, the NIHR or the Department of Health and Social Care.

This research was reviewed by a team with experience of mental health problems and their carers who have been specially trained to advise on research proposals and documentation through the Feasibility and Acceptability Support Team for Researchers (FAST-R): a free, confidential service in England provided by the National Institute for Health Research Maudsley Biomedical Research Centre via King's College London and South London and Maudsley NHS Foundation Trust.

Finally, we would like to thank all members of the RADAR-CNS patient advisory board, who all have experience of living with or supporting those who are living with depression, epilepsy or multiple sclerosis.

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