





Requirements Elicitation and Modelling of Artificial Intelligence Systems: An Empirical Study

Khlood Ahmad¹^a, Mohamed Abdelrazek¹^b, Chetan Arora²^c, John Grundy²^d and Muneera Bano³^e

¹Deakin University, Geelong, VIC, Australia

²Monash University, Clayton, VIC, Australia

³CSIRO's Data61, Clayton, VIC, Australia

{ahmadkhl, mohamed.abdelrazek}@deakin.edu.au, {chetan.arora, john.grundy}@monash.edu, muneera.bano@csiro.au

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Abstract: Artificial Intelligence (AI) systems have gained significant traction in the recent past, creating new challenges in requirements engineering (RE) when building AI software systems. RE for AI practices have not been studied much and have scarce empirical studies. Additionally, many AI software solutions tend to focus on the technical aspects and ignore human-centered values. In this paper, we report on a case study for eliciting and modeling requirements using our framework and a supporting tool for human-centred RE for AI systems. Our case study is a mobile health application for encouraging type-2 diabetic people to reduce their sedentary behavior. We conducted our study with three experts from the app team – a software engineer, a project manager and a data scientist. We found in our study that most human-centered aspects were not originally considered when developing the first version of the application. We also report on other insights and challenges faced in RE for the health application, e.g., frequently changing requirements.

1 INTRODUCTION


There has been a massive shift towards using Artificial Intelligence (AI) components in software solutions. This shift has been possible because of the increase in processing power, better AI models, and the availability of large datasets to train accurate AI models (Holmquist, 2017). However, incorporating AI components has impacted how we build software systems, and new issues have emerged in the software development process.


Existing methods and tools used in Software Engineering (SE) are often inadequate in building AI software (Sculley et al., 2015; Feldt et al., 2018). Most AI models rely heavily on the training data, have inherent inaccuracies, unpredictability, and are largely black-box in nature. These attributes have led to new requirements, usually not considered or emphasised in traditional SE, such as AI-based software ethics and


data requirements (Martínez-Fernández et al., 2022). In traditional Requirements Engineering (RE), i.e. without an AI component, the process usually involves specifying requirements for systems that are deterministic, and the outputs are known early on. In RE for AI (RE4AI), it is more difficult to specify requirements for non-deterministic and black-box components, for which the outputs are usually unknown until the models are trained and tested with data (Belani et al., 2019; Agarwal and Goel, 2014; Khomh et al., 2018). However, requirements such as policies, business values and system constraints need to be established at early stages (Ezzini et al., 2023).


AI-based software development has mostly focused on the technical aspects of the AI components (Maguire, 2001; Schmidt, 2020) and overlooked human-centred aspects, such as age, gender, culture, emotions, ethnicity, and many others (Grundy, 2021; Shneiderman, 2022; Fazzini et al., 2022). Lu et al. (Lu et al., 2022) interviewed 21 AI scientists and engineers and found that responsible AI requirements were overlooked or only included at very high-level system objectives. Overlooking these human-centred aspects when building AI soft-

^a <https://orcid.org/0000-0002-7148-380X>

^b <https://orcid.org/0000-0003-3812-9785>

^c <https://orcid.org/0000-0003-1466-7386>

^d <https://orcid.org/0000-0003-4928-7076>

^e <https://orcid.org/0000-0002-1447-9521>

ware can lead to systems that are biased, discriminate against user groups, and are non-inclusive (Amershi et al., 2014).

In this paper, we build on our existing work on a structured literature review (SLR) on RE for AI systems (Ahmad et al., 2021; Ahmad et al., 2022), a survey on practitioners' perspective on RE for AI systems (Ahmad et al., 2023), an RE framework for eliciting and modelling human-centric AI software requirements. In this paper, we report on a case study we performed on a tool implementation of our framework on a mobile health application (MoveReminder-App) that encourages people with type-2 diabetes to move more. We shared the tool with three experts from the team working on the mobile application to elicit and model the requirements. We then interviewed the experts for feedback on the tool and framework and report on the findings in this paper.

Our study found that most of the human-centred aspects were not considered in the development process. In RE for AI systems, it is difficult to specify certain requirement types at the early stages of the development process, as data requirements and model requirements usually have to be adjusted or changed for the model to achieve desirable outcomes. However, our framework can help address some of the issues during the early stages of the development process, e.g., addressing human-centred issues and thinking about the data and model requirements. Based on our findings from this case study, we propose that a progressive and iterative agile method could be more appropriate to adopt. Furthermore, using our framework and the tool can help capture requirements changes as stakeholders learn more about the problem, data and potential models in the early stages of development. We note that RE for AI is a relatively new area of research, and empirical studies in this area are extremely scarce. This paper and our case study findings contribute to the empirical evidence on performing RE for AI.

The rest of the paper is structured as following: Section 2 presented the related work. Section 3 presents details of our framework and the tool. Section 4 reports on the details of our case study. Section 5 presents the outcomes of our sessions with experts on MoveReminderApp study. Section 6 discusses key results from the interviews and summarizes reflections from our study. Section 7 concludes.

2 RELATED WORK

Requirements elicitation is considered the most crucial part of RE as it sets to unravel and capture the need for the system from the stakeholders early on in the software development life cycle (Davey and

Parker, 2015). The process of eliciting requirements includes “a set of activities that must allow for communication, prioritization, negotiation, and collaboration with all the relevant stakeholders” (Zowghi and Coulin, 2005). In order to capture the correct requirements, system boundaries need to be set and defined (Nuseibeh and Easterbrook, 2000).

The techniques used in eliciting requirements can vary from formal and informal interviews, surveys and questionnaires to other tasks such as scenarios, observations and protocol analysis (Carrizo et al., 2014). Several presenting issues related to requirements elicitation techniques include miscommunication and difficulties in transferring knowledge between the elicitor and stakeholder (Fuentes-Fernández et al., 2010). These issues involve eliciting: (1) *known unknowns* referring to knowledge of which the requirements engineer is aware of but not the stakeholder. (2) *unknown knowns* refers to the knowledge held by the stakeholder but not expressed to the requirements engineer. (3) *unknown unknowns* are the most challenging of all, wherein both the stakeholder and the requirements engineer are not aware of the existing knowledge in this situation (Sutcliffe and Sawyer, 2013; Gervasi et al., 2013). There are many unknown-unknowns in RE4AI, especially during the early stages of exploring AI software. Most AI-based projects lack a common understanding of what requirements are needed to build the project, with limited shared knowledge among the stakeholders and the team building the AI software, making it difficult to elicit and specify requirements. The unknowns include the outcomes of the system that may only be known once the model is trained on a given dataset. Thus, some requirements can only become known towards later stages of the software life-cycle.

Requirements modelling languages are used to visually display requirements and identify the stakeholders' needs at a higher-level system abstraction (Gonçalves et al., 2019). The examples of RE modelling languages include Goal-Oriented Requirements Languages (GRL) (Lapouchnian, 2005) and the *i** model (Dalpiaz et al., 2016). In GRL, goals are used to model non-functional requirements (NFR) and business rules (Amyot and Mussbacher, 2011). However, the disadvantage of using GLR is that it is difficult to learn among non-software engineers. Modelling languages such as UML and SysML have been used to model requirements in RE4AI. Although these modelling languages are easier to use and learn than GRL, they have limitations in modelling NFR's and business rules (Ries et al., 2021; Gruber et al., 2017; Amaral et al., 2020). Other studies proposed to use of conceptual models to present requirements in

RE4AI (Nalchigar et al., 2021).

Existing tools used to support software engineers in developing human-centred AI software include the “Human-AI INtegration Testing”(HINT) tool (Chen et al., 2022) and the “AI Playbook” (Hong et al., 2021) that provides early prototyping to reduce potential errors and failures in AI software. Although these tools support building human-centred AI software, they are limited to the design phase and not to RE. Additionally, the tools found in the SLR, such as the GR4ML (Nalchigar et al., 2021) to visually present and model requirements for AI software systems did not focus on the human-centred aspects in their prototypes.

3 RE4HCAI FRAMEWORK

We proposed framework (RE4HCAI) for guiding the requirements engineers and other stakeholders in requirements elicitation and modelling of human-centered AI-based software. The framework has three layers, as shown in Figure 1 and discussed below.

Identifying Human-centered AI components. The first layer consists of six categories of requirements that need to be elicited for developing human-centered AI software solutions. The six areas are User Needs, Model Needs, Data Needs, Feedback and User Control, Explainability and Trust, and Errors and Failure. The categories are inspired by Google PAIR’s human-centred AI guidelines (Google Research, 2019). Our categorization into six areas aligns with the five categories proposed by Google PAIR (all areas except Model Needs). We added the ‘Model Needs’ that identify the human-centered approaches used when selecting and training an appropriate AI model. Figure 2 shows a high-level summary of the requirements covered in each area.

Requirements Catalog. For each of the six areas, we combined the human-centred guidelines from Google PAIR, Microsoft’s guidelines for human-centred AI interaction (Microsoft, 2022), and the guidelines for Apple’s human interface for developing ML applications (Apple Developer, 2020) along with the Machine Learning Canvas (Louis Dorard,). Next, we then collected all requirements in the literature (Ahmad et al., 2022; Villamizar et al., 2021) that fit our six selected areas and mapped them against the combined guidelines. To validate our mapping, we conducted a survey with practitioners to understand which of these six areas (and the guidelines in Figure 2 should be included in a RE4HCAI framework (Ahmad et al., 2023). The results showed that all the six areas in the RE4HCAI framework are deemed important by practitioners when collecting AI

requirements. The gathered human-centred requirements were listed in a tabular format to form our catalog, with six sections. Each section is dedicated to eliciting detailed requirements for each area of Figure 2.

Conceptual Model. Our SLR reviewed papers that used a modeling language or notation to present requirements. We found that most of the studies preferred UML or a conceptual model. UML was a preferred choice because it is easier to understand and use among different groups. However, UML has some limitations when presenting requirements for AI and lacks direct support for modeling business rules and NFR’s (Ahmad et al., 2021). Also, in our RE4HCAI we have concepts that are difficult to visualize in UML, such as needs, limitations, and trade-offs. Therefore, we created a conceptual model which can be instantiated in a project to present the requirements visually.

Our modeling language consists of two layers. The first layer provides a holistic view of each of our six areas. We show part of this model in Figure 5. In the first layer, we use UML class notations to showcase a high-level presentation of the requirements needed for each area and an oval shape to show the system’s high-level goal and connect all six presented areas. The second layer presents a separate model for each area, and we use unified notations for all the areas as illustrated in Figure 3. When creating our modeling notations, we tried to adhere as much as possible to the Physics of Notations (Moody, 2009). We incorporated different shapes, colors, and textures to reduce cognitive overload for users and make the notations easy to use and understand. Each notation is used to model a different concept from the requirements collected in the requirements catalog.

3.1 RE4HCAI Collaborative Tool

Developing a software system with an AI component requires different teams and roles to work together. In order to facilitate collaboration between the development teams, we aimed to develop a collaborative tool for implementing our framework. The idea was to use platforms that are familiar among different AI-software development roles, and utilize existing tools and collaboration platforms. As part of our practitioner survey (Ahmad et al., 2023), we asked the participants about their platform preferences. Based on the survey results, we identified platforms to use for evaluating our initial prototype. We use Confluence (<https://www.atlassian.com/software/confluence>), an online collaboration platform where team members can work on projects together and share, plan and build ideas together. Confluence is used as a mean

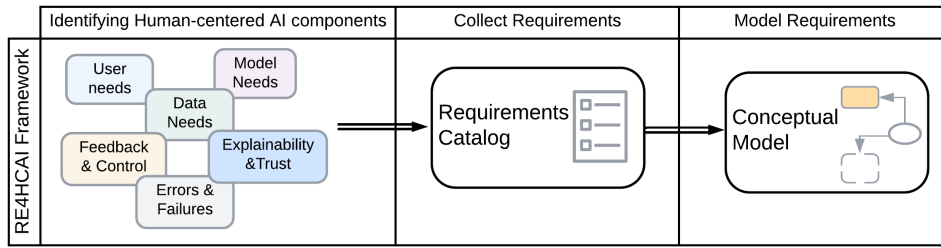


Figure 1: Framework for eliciting and modeling requirements for human-centered AI software

User Needs	Model Needs	Data Needs
<ul style="list-style-type: none"> Identify the user Identify the need Users expectations Understand limitations Feasibility of AI Automation vs Augmentation Trade-offs (reward function) Determine AI features 	<ul style="list-style-type: none"> Optimize algorithm for? Task used (regression, ...) Training method Balance overfitting & underfitting Tools to evaluate model How is training data used How is feedback used 	<ul style="list-style-type: none"> Data sources Split data Number of samples required Data labeling (if required) Features in datasets Data accuracy Data privacy Identify biases in data
Feedback & Control	Explainability & Trust	Errors & Failures
<ul style="list-style-type: none"> Implicit feedback Explicit feedback Monitor user behavior Privacy - collecting feedback How feedback improves AI Feedback used in model tuning When user take control? How users adjust preferences 	<ul style="list-style-type: none"> Explain limitations & capabilities Explain consequences Explain data Explain output How much detail to provide When not to explain Explainability will conflict with? Explain how user info is used 	<ul style="list-style-type: none"> Specify errors (contexts, system, ...) Specify error source Get feedback to user rejections Avoid errors made on sensitive data Allow user to fix mistakes lookout for abusive users

Figure 2: Requirements for Human-Centred AI.

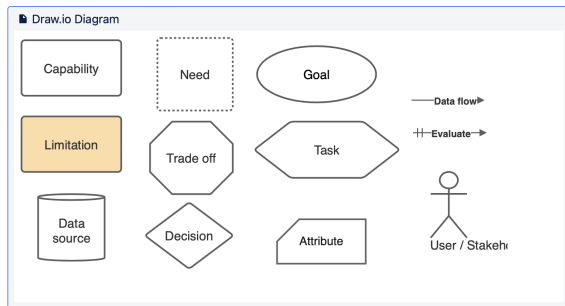


Figure 3: Legend for the conceptual model at the second level to show more abstract requirements

to present our framework among participants and allows us to present our modelling tool using the existing drawing applications Draw.io (<https://drawio-app.com>).

The platform contains a template project space as shown in Figure 4. The landing page provides an overview of the platform, framework, and a short tutorial on how to use the catalog and the modeling language. The main page further contains six sub-pages each dedicated to part of the framework. Sub-page one includes a table with the catalog for eliciting the human-centered requirements for a specific AI-software system. Sub-page two showcases the avail-

able modelling notations that are displayed in Figure 3. Sub-page three contains the template model for the first layer model. The last three sub-pages provide templates for the models second layers. We only provide models for the first three areas at this stage, i.e., “User Needs”, “Model Needs”, and “Data Needs”, and plan to expand it further in the future.

4 CASE STUDY DETAILS

We conducted a case study to investigate the usefulness of our framework and the corresponding platform to engineering AI software with a human-centered perspective. Our case study the MoveReminderApp project (Daryabeygi-Khotbehsara et al., 2022), involved designing and building a real-time health application for people with type 2 diabetes (T2D). The application keeps track of the users’ behavior toward movement, measures the sedentary time, and sends notifications to remind the user to move. These notifications consist of messages using a Deep Learning (DL) model to remind the person to stand up or walk once the user has been predicted as sitting for a prolonged time.

We conducted our case study with three experts who worked on the MoveReminderApp project, in-

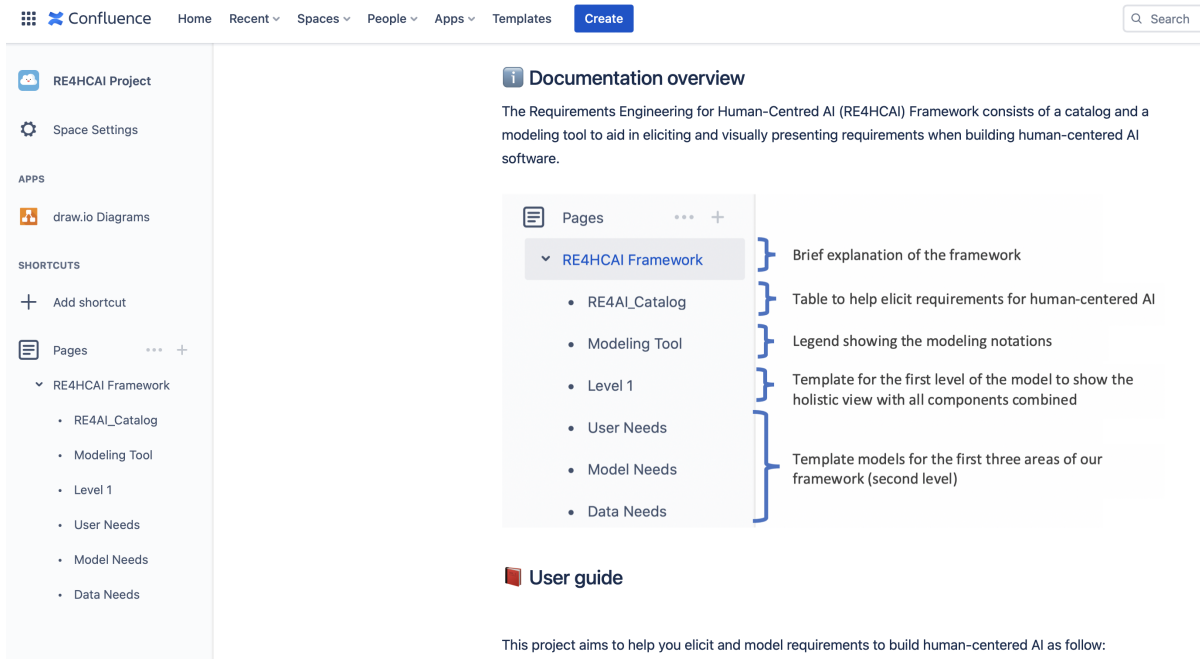


Figure 4: The Confluence collaboration page used to conduct the case study

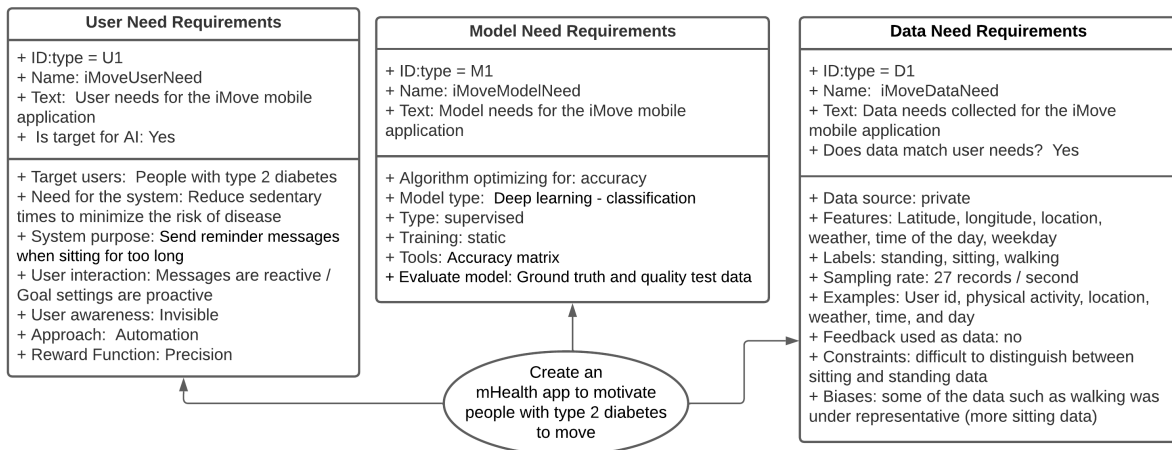


Figure 5: Model presenting a holistic view of the requirements elicited for the MoveReminderApp project.

cluding a project manager, data scientist, and software engineer. Our participants have several years of professional experience: the project manager has nine years of experience, the software engineer has two years of experience, and the data scientist has four years of experience in their field. We note that getting these three experts in our case study provides complimentary views and perspectives from different roles in AI-based software development. Also, the MoveReminderApp project was already in the late development stages and was intentionally selected as we wanted to investigate if the experts had initially con-

sidered different aspects of our framework while eliciting and specifying or modeling requirements.

Requirements Elicitation Sessions. We created a dedicated project in Confluence for the MoveReminderApp project, giving each participant access to the project. We first conducted a session with each participant. Due to the workplace recommendations and experts' preferences, all sessions were conducted virtually. The sessions were for 1-2 hours each. Each session was dedicated at making the participants aware of our framework and the Confluence platform and using their domain knowledge and expertise in

the MoveReminderApp project to investigate if our platform was valuable for their project’s context. We further wanted to identify any discrepancies between the participants’ views of the requirements needed for the first three sub-areas in our framework. To do so, we elicited requirements using the catalog from each of the three participants individually.

Once all the requirements were elicited, a holistic view of the MoveReminderApp project was established, as shown in Figure 5, and a model was created for each of the three areas as described in the next sections. We note that we used our requirements catalog of Figure 2 to elicit information for each of these three areas. Participants could return to the Confluence project at any time and edit the elicited requirements and models.

Participant Interviews. The final step in our study involved interviews with the participants to get their feedback on our platform and the framework. We note that the data scientist in the project was not available for the interview stage due to personal reasons, and only the software engineer and the project manager participated in our interviews. We obtained consent from both participant’s, and interviews were carried out online. Due to the limited availability of the experts, the two interviews were scheduled for 45 minutes each. Both interviews were audio-recorded and transcribed for analysis and evaluation.

5 ELICITATION SESSIONS

In this section, we provide details of the outcomes of our requirements elicitation and modeling sessions with the three participants. Below, we discuss the outcomes of eliciting requirements for the user needs, model needs, and data needs collated from the three sessions. Figure 5 presents the high-level requirements for the first three areas and the main goal for the project. When building the models, we used a blue tick to distinguish between framework requirements and system requirements, as shown in the first three models in Figures 6, 8, and 7. The notations that do not have a blue tick are specific to the MoveReminderApp project.

5.1 MoveReminderApp: User Needs

We identify the need for the system as shown in part **a** (the blue colored box) in Figure 6. The experts had considered, among others, previous scientific literature on the behavior of T2D patients to determine *the need for the project*. A recent SLR showed that people with T2D have higher sedentary behavior, which can cause serious health risks (Kennerly and Kirk, 2018). The existing literature found that getting

people with T2D to break up their sitting time with little movements could improve quality of life and reduce increased health risks due to diabetes (Dempsey et al., 2016). Using digital health solutions, such as sensors, wearables, and mobile phones, was found to reduce sitting times to 41 minutes per day (Stephenson et al., 2017).

When evaluating the need, it was evident that minimizing prolonged sitting times could reduce the risk of increased blood pressure, high cholesterol, and cardiovascular diseases, specifically for people with type 2 diabetes (Daryabeygi-Khotbehsara et al., 2022). The idea behind using a mobile health application was to generate notifications by the system as to when to stand up. Therefore, the system will have to accurately predict if the user has been sitting too long and notify them to stand up or walk around. Since the application had to provide predictions, using AI (i.e., machine learning or deep learning) was a feasible solution. Figure 6 shows the system’s different needs (part **a**), including improving mental health as an outcome of breaking up prolonged sitting times for people with T2D. Part **b** (the green colored box) of Figure 6 shows what the system is used for.

In part **c** (the red colored box) of Figure 6 we show the limitations and capabilities of the system. There were several *system limitations* that were identified early, and some of these limitations appeared as the project advanced in the later stages. Some of the limitations were easily addressed, e.g., delays in users receiving messages from the application and connection issues between the sensors and the application. Other system limitations were difficult to address. These included goal settings, as the model could not achieve this feature. Therefore, the user had to input the settings manually through the user interface. Also, part of the initial plan was to include behavioral change techniques (BCT), such as mood. However, this was later discarded as they found that including BCT features would increase the number of messages sent to the user, making it more of a hassle and an inconvenience to the end user.

When evaluating the *reward function* or evaluation metric, we first set out to list the possible outcomes of getting either a False Positive (FP) or a False Negative (FN), as reflected in Part **d** (the purple colored box) of Figure 6. We discussed these options and *weighed out the trade-off*. An FP meant the system would send a message to remind the user to stand up or walk when they were already standing or walking. An FN happened when the person was sitting for too long, and the application would miss sending a reminder. In the case of an FP, the end user would lose interest in the system if incorrect notifications were sent and most

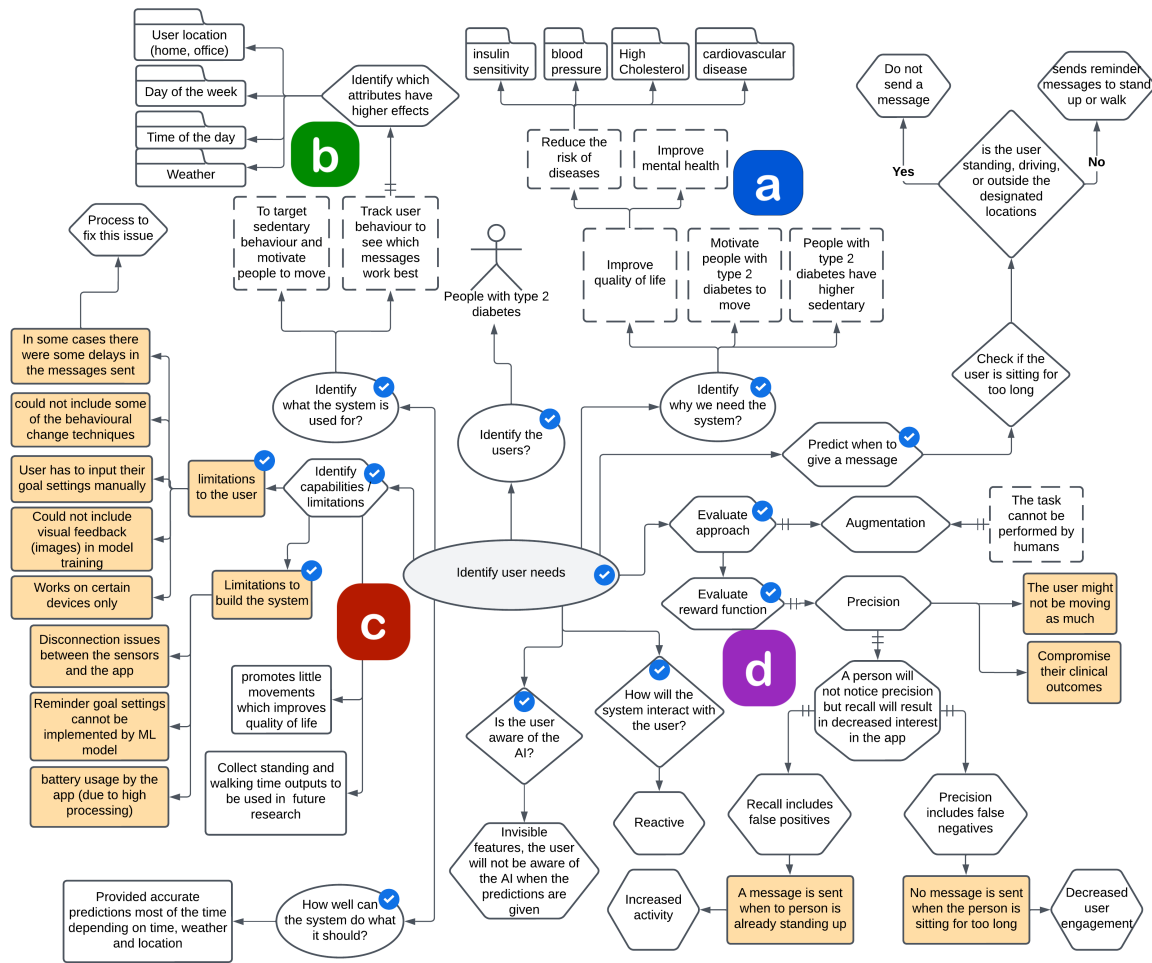


Figure 6: User Needs for the MoveReminderApp project

likely become less interested in using the application altogether. Contrarily, when an FN occurs, the end user would not notice, as sitting is part of human nature. The downside to an FN was that the user would move less than required, which might complicate or delay their clinical goals. However, the project manager explained that from the user's perspective, having an FP had higher consequences than an FN, as an FN would not irritate the end user as much as having an FP. Thus, the aim was to minimize FP as much as possible when selecting the reward function.

5.2 MoveReminderApp: Model Needs

The deep learning (DL) model was designed to *optimize for accuracy*. Although we established in user needs that precision would be the evaluation metric, the predictions were evaluated based on accuracy only by the experts when building the model. The selected *DL classification model* was built to distinguish

a person's movement behavior. Initially, the training was done offline by collecting data from sensors manually and using this data to train the model. Therefore, the model was not designed to learn and adjust to users' behavior while using the system. Figure 7 shows part of the model-needs model developed for the MoveReminderApp project.

Most of the *model tuning* happens at the data level for this project. When training the model, there were enough data instances, and the data had ground truth, thus making it easy to train the model. However, the experts expressed that while using the training data, the model could not distinguish between standing and walking instances. This issue was mainly due to the data collection method, as each data-collection instance had 27 sensor data records per second. One second's worth of data for each instance was not enough for the model to detect the users' movement when it came to standing and walking. To fix this is-

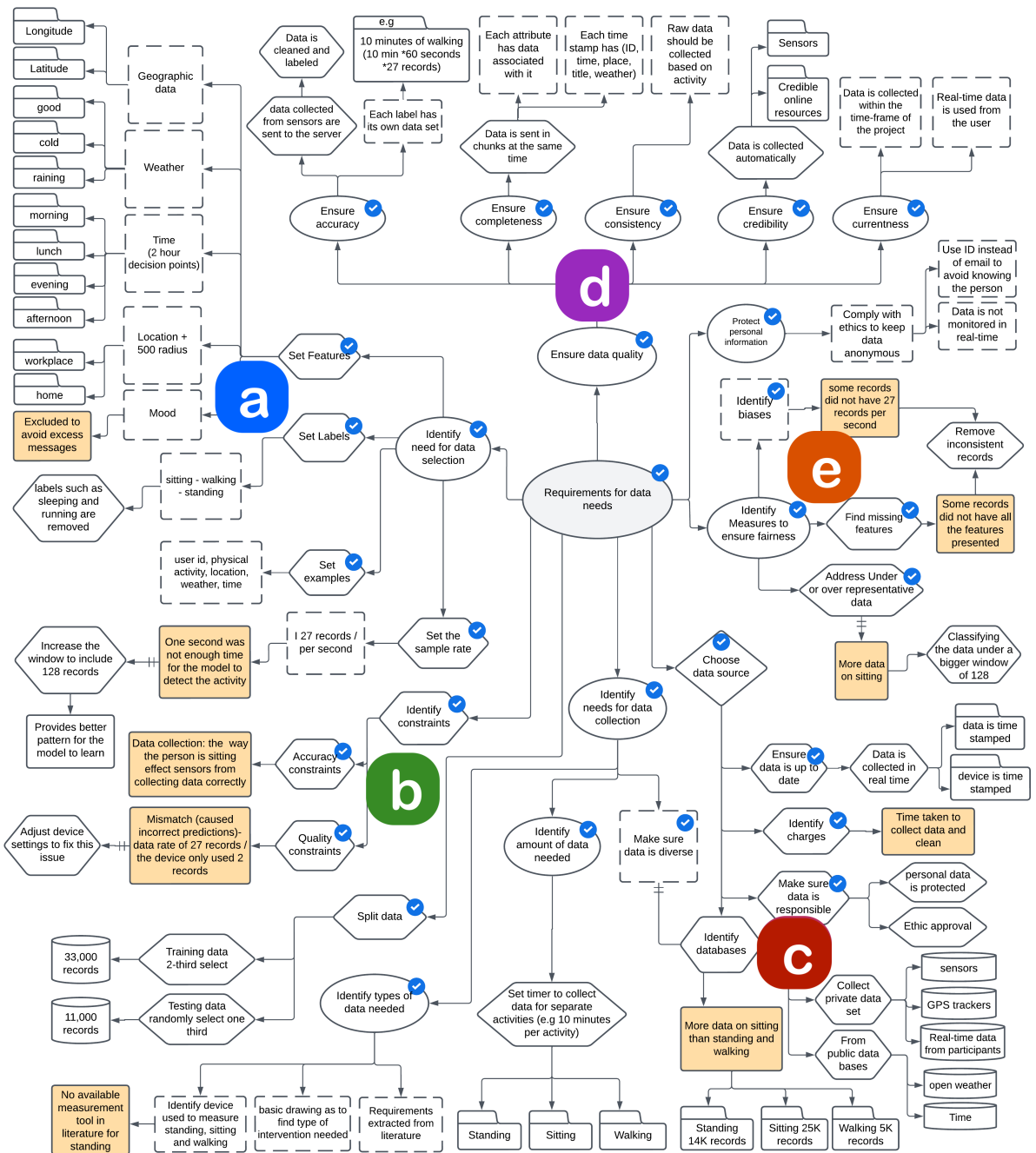


Figure 8: Data Needs for the MoveReminderApp project

ethics application while collecting and using personal information. The team mentioned that it was challenging to make sure that the users' personal information was protected. They ended up providing each user with an ID and did not collect data from users in real-time to keep them anonymous. The next step was to find any missing features. When cleaning the data, they found that some instances did not have 27

records per second, which caused inconsistencies in the data. Also, the data on walking and standing was underrepresented, which caused issues in the accuracy of the predicted results.

6 INTERVIEWS

We asked the MoveReminderApp team for feedback on our proposed RE4HCAI framework and its

supporting collaborative tool. Below, we present their feedback on the framework and the tool and present some insights from applying our framework to the MoveReminderApp project.

6.1 RE4HCAI Framework Feedback

Collaborative work. Both experts highly rated the ability to work collaboratively on the platform. The project manager felt that it was an excellent choice to use Confluence. They explain that *“using confluence compared to other platforms that I had used before such as Jira was easier to learn”*. They also felt that having such a platform could help shorten the duration of the study and make everything much clearer.

Visual Aspects. Both experts said that the model’s key advantages include providing a practical visual representation of the system’s AI-based component requirements. Using yellow for limitations was favored by our participants. One participant mentioned that *“limitations are negative, and having it colored yellow made it easier to distinguish”*. Also, using notations such as icons, database notations, and decisions was convenient as they could quickly point them out without needing to go back and check the legend.

Limitations. We asked our participants about the limitations of the catalog and modeling language. The project manager explained that they had issues understanding some of the terminologies used in the catalog. *“I had some questions, and some aspects I did not understand as I am not from an engineering background, but you clarified those for me.”* They suggested we provide examples to the catalog to explain the concepts and include a comment section to provide feedback when required. The major limitation of the model was that it could get slightly complex at times. For example, in the data needs model, a lot of information was presented, and it got difficult to keep track of the information provided. Suggestions to reduce the complexity of the final models included slicing the model into smaller parts or highlighting aspects of the diagram based on how it is categorized.

6.2 Reflections

Missing Requirements. We noticed that the human-centred aspects presented in our catalog were not considered when originally building the MoveReminderApp, especially the user needs area. Our participants said they had to re-consider most of the user needs only after viewing the models. Requirements such as evaluating the reward function were not discussed among the team members when building the project. For example, they did not consider the consequences of having a FP vs a FN in the app before starting the project. This reflects the need for a platform like ours

to help guide the practitioners in eliciting and modeling requirements when building AI software.

New Roles, Collaboration and Communication. AI paradigm has introduced new roles and requirements, which was not the case in traditional software engineering projects. For instance, we noticed that some of the requirements extracted from the project manager were not in line with the requirements taken from both the data scientist and software engineer. We used our framework and tool to assist the team in clarifying these crucial requirements issues.

For example, when we collected requirements from the project manager, we established that precision should be used when evaluating the reward function. However, the data scientist working on the DL model focused on accuracy. Accuracy might not have been the best metric to use as high accuracy could have been achieved if the negative class was the dominant one (Juba and Le, 2019). This would have caused issues in the results, as there was a visible class imbalance in the dataset. Class imbalance is when data from the major class is more represented than the other classes, which can cause the model to present biased results towards the dominant class (Johnson and Khoshgoftaar, 2019; Japkowicz and Stephen, 2002). In this case, data on sitting was more represented than standing and walking, which might have contributed to the high accuracy.

We observed that in some instances, the different team members were unaware of some aspects the other members were working on prior to introducing our tool. For example, the data scientist had to adjust the amount of data fed into the model to 128 records due to model limitations. The project manager became aware of this only after observing this limitation in our conceptual model. Also, the software engineer was only aware of setting up the sensors and collecting the data from the devices and was not able to provide much detail on what features were needed for the data, such as time and weather.

Changing Requirements. Another observation we made was that some of the MoveReminderApp project requirements changed over time. For example, in terms of user needs, some of the system needs were found to be difficult to implement due to model limitations. The original plan was to include images when displaying the feedback to the end user. Over time, it became apparent that the model had limitations and could only provide textual messages. Thus, providing visual feedback became a limitation to the system rather than a need. Also, when collecting data requirements at the start of the project, it was not very clear how the data should be used to train the DL model. Initially, there was a lot of raw data to

work with. However, the format and the diversity of the collected data were not adequate to use for training or testing the model. The data had to be modified throughout the project timeline on many occasions for it to become fit to train the selected model. This reflects the volatility and the exploratory nature of AI projects. Thus a platform like ours facilitates discussions in the early project stages to establish foundational requirements, which all roles agree on. This would help deal with the changing requirements as well, and to see the impact of the changes on different parts of user needs, model needs or data needs.

7 CONCLUSIONS

In this paper, we reported on a case study related to our framework and the related tool for eliciting and modeling requirements for human-centred AI. The tool is used to support our proposed framework based on the industrial human-centred guidelines, an analysis of studies obtained from the literature, and a user survey that we have conducted. The case study was conducted with three experts from a team working on a mobile health application targeted at type-2 diabetes patients. We found that most human-centred aspects were missing from the initial planning of the AI software solution. Also, we found that requirements change dramatically over time with AI software, and a more iterative approach to RE needs to be considered. In the future, we plan to conduct more case studies of our framework and the tool. Specifically, we aim to select projects using different AI techniques, from different application domains, and at different stages of development. We want to investigate the difference in the RE process with and without our framework, in different settings.

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