NeighbourhoodBot: connecting communities with conversational agents

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4th July 2024

A thesis submitted in partial fulfillment of the requirements for the degree of Bachelor of Science in Artificial Intelligence

Vrije Universiteit Amsterdam

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Abstract

NeighbourhoodBot is a conversational agent designed for neighbourhoods, aiming to enhance connectedness by linking individuals with potential helpers, prompting users to share skills, and providing guidance on community initiatives. This paper reviews relevant literature and includes a pilot study examining the essential design and implementation choices for such a chatbot. Furthermore, it presents an evaluation of the chatbot's effectiveness in fostering community engagement based on a user study. NeighbourhoodBot produces accurate and appropriate responses and effectively facilitates connections between those seeking assistance and those able to provide it. Moreover, questionnaire results confirm that NeighbourhoodBot significantly enhances civic engagement by boosting users' sense of responsibility, care, and contributions to their neighbourhood. This paper recognizes the importance of strengthening community bonds as a means to address broader societal challenges and highlights the potential of conversational agents to aid the way communities interact, engage, and solve problems together.

1 Introduction

This paper presents the design and evaluation of NeighbourhoodBot, a chatbot aimed at enhancing neighborhood connectedness and engagement, motivated by the widespread sense of disconnection in urban areas. The introduction outlines the problem of disconnection, loneliness, and depression, explores practical solutions for community development and assesses the role of chatbots in this context. Based on this, the research questions of the study are detailed, along with the methodology used to approach this research.

1.1 Loneliness, depression and disconnection

In modern Western urban environments, a sense of disconnection between individuals and their neighbourhoods is increasingly evident, highlighted by declining social interaction rates and reduced civic engagement. A 2018 U.S. study, for instance, revealed that only 24% of urban residents knew their neighbours [32] and this lack of connection extends to civic participation, with only about a third of people voting in local UK elections in 2021 [47]. Trust within communities has also significantly diminished; in 1972, about 45% of Americans felt they could trust others, but by 2016, this number had fallen to roughly 30% [31, 16], reflecting a deepening scepticism in interpersonal relationships. Furthermore, loneliness is influenced by this widespread disconnection; Johan Hari [21] argues that modern society has created environments that isolate people, leading to widespread feelings of loneliness and depression. This isolation is illustrated by the General Social Survey, which reveals that the number of people with no one to discuss important matters has tripled between 1985 and 2004 [29, 16]. Even before the COVID-19 pandemic, three in five American adults considered themselves lonely [10]. Loneliness, while distinct, is part of the larger narrative of community disconnection [21] which lies at the heart of many of society's challenges [40]. This paper recognizes the value of strengthening community bonds for addressing societal issues.

1.2 Practical solutions toward community connectedness

Research into community development highlights the effectiveness of focusing on "what's strong, not what's wrong," [40] advocating for the empowerment of residents through the recognition of their individual skills. For neighbourhood members to achieve collective success, they must experience a sense of empowerment [3], possess immediate and actionable steps [9], and engage in actions that have quick and meaningful impact [14]. Furthermore, it is essential for residents to be well-informed [9] about their community, including strategies for mobilising local assets [26, 28]. Emphasising skills does not negate the importance of addressing problems; rather, it highlights that problem-solving is achieved by connecting their neighbourhoods in sharing collective strengths. By leveraging their individual skills and fostering connections among neighbours, communities can collaborate effectively, share resources, and support one another, ultimately prioritising their collective needs [14].

1.3 The potential of chatbots in community development

Chatbots can be task-based, informative, and conversational [8]. While research has demonstrated chatbots' roles in collective group organization, encouraging action, being informative, and problem-solving [25, 46, 35, 30], their potential to combine these roles to motivate neighbourhood connections remains unexplored. This research study explores whether chatbots can serve as tools for encouraging community action by providing information on neighbourhood development, offering solutions and advice for specific problems, and generating innovative ideas with actionable steps tailored to users' skills. Additionally, this study examines the role of chatbots as intermediaries between individuals seeking assistance and those willing to provide support within a neighbourhood.

1.4 Research questions

The following research questions therefore guide this study:

RQ1: How does research into community development and conversational agents inform the design of a chatbot aimed at enhancing neighbourhood connectedness/engagement, and how can these design choices be accurately implemented?

RQ2: Do conversational chatbots that focus on community development content increase users' sense of responsibility, care, and contributions to their local neighbourhood?

RQ3: Can conversational chatbots that store and relay users' requests for assistance (e.g 'It is too noisy in my area', 'I want more green spaces') effectively facilitate connection between individuals seeking help and those willing to provide it?

Assumption: *Members of a neighborhood are connected through a digital forum where they can share posts, petitions, and fundraisers, and message each other. This platform enables users to take* *immediate and accessible actions.*

1.5 Approach

Our approach focuses on the design and evaluation of NeighbourhoodBot, a chatbot aimed at enhancing community connectedness. Informed by an extensive literature review detailed in Section 2.2 to address Research Question 1 (RQ1), the chatbot employs rule-based systems, vector embeddings, large language models, and a multiclass classifier. These technologies guide users through customized conversation flows, enabling NeighbourhoodBot to accurately identify user needs and suggest actionable steps. The initial effectiveness of the chatbot is tested in a pilot study, as outlined in Section 4.1. This study helps refine the design and implementation for the user research study, detailed in Section 4.2. During this user study, participants interact with the bot under controlled conditions to assess its ability to recognize user intentions, match problems with appropriate skills (addressing RQ3), and engage citizens effectively (addressing RQ2). The evaluation of this study not only tests the chatbot's functionality but also examines the effect on its users and its potential to foster a sense connectedness among community members.

2 Literature review

2.1 Related work

This section describes literature relevant to this research study, focusing on chatbots in organizing groups, supporting mental health, and encouraging user action; all of which are necessary tasks for NeighbourhoodBot. Additionally, it examines current research on community development and the application of AI in local governance. Excluded from this review are studies on conversational agents with dissimilar design outcomes, community development research that does not emphasize resident empowerment, and AI in local governance research that involves privacy-related grey areas.

2.1.1 Chatbots in group organisation

Studies exploring the use of chatbots within group discussions [25] for managing time, encouraging dialogue, and summarising text have demonstrated that integrating chatbots leads to more effective communication. TaskBot [46] is tailored to monitor conversation within work settings to store meetings, deadlines, and other organisational tasks stemming from these interactions. It displays an ability to extract specific information relevant to its future task.

2.1.2 Chatbots in mental health

The application of chatbots in mental health, as demonstrated by ChatPal [35], offers insights into how chatbots can be designed to address mental health needs in rural areas. The study focuses on gathering strategies, personalities and scripts that would be optimal for a chatbot of this kind. With loneliness so closely tied to conversations about community disconnection, empathetic personality traits of this kind are relevant. Adding to this, research presented in the study by Fitzpatrick et al. [19] explores the use of the chatbot "Woebot" in delivering cognitive behavioural therapy sessions.

2.1.3 Chatbots encouraging action

The "Climate Bot 1.0" [30] demonstrates how chatbots can engage users in environmental responsibility, going beyond providing information by actively motivating sustainable practices. Similarly, research on chatbots for recycling [50] explores how these tools can encourage better recycling habits through positive reinforcement.

2.1.4 Research into community development

Phil McNight and Cormac Russell [40, 26, 28] advocate for a strengths-based approach to community development, which prioritises leveraging existing strengths in neighbourhoods rather than initially focusing on problems. Additional research into the significance of citizen engagement and methods for activating it [9, 14] also outlines practical steps and strategies for community leaders to achieve this goal.

2.1.5 AI and data in local governance

Research on AI in local governments [48] primarily focuses on the use of data analytics and machine learning to aid decision-making and streamline office operations. It also emphasises the role of chatbots in providing real-time information and services to residents, such as the MyGov Corona Helpdesk [12], an Indian chatbot created to offer accurate information and advice during the COVID-19 pandemic.

2.2 Design and implementation review

This literature review examines the essential design and implementation choices for developing a conversational chatbot aimed at enhancing community engagement. The overarching research question guiding this review is:

RQ1: How does research into community development and conversational agents inform the design of a chatbot aimed at enhancing community connectedness/engagement, and how can these design choices be accurately implemented?

2.2.1 Design choices

Within the research field of community development, there is a prevailing idea to focus on "what's strong" in a neighbourhood rather than "what's wrong" [40]. This concept, known as Asset Based Community Development (ABCD) [26, 28], encourages citizens to mobilise available resources and skills to enhance their local economy and engagement. The ABCD approach highlights five assets which are involved in community initiatives: *local residents* (skills, experience, motivation), *local voluntary associations*, *local institutions*, *physical assets*, and *economic assets*, configured from 2000 cases where neighbourhood residents responded to the question, "Can you tell us what local residents have done together that has made things better" [28]. Research indicates that leveraging local skills and resources enables communities to address their needs more effectively [33]. Therefore, the chatbot should encourage action, prompt the user for skills and interests and provide practical advice based on this information, leveraging their skills towards community action and connectedness.

To engage community, there must be available quick and impactful solutions to empower citizens [9, 14]. Providing practical steps and immediate actions fosters a sense of control, ownership and empowerment [3] among community members. Given this, it is crucial to decide what solutions are available for a local resident to immediately take action. The chatbot holds the assumption that members of the community are connected via a digital forum, therefore the system can utilise this to offer a set of immediate actions. Kimport et al. [18] demonstrate the potential of the web for enabling collective actions such as group formations, event organisation, petitions, and fundraisers. Moreover, shared experiences and storytelling are critical in fostering a connected community, as highlighted by Cormac Russell [40], and should be considered as a potential action for a resident to take. Furthermore, options such as consulting further expertise or engaging in freelance activities should also be suggested by the chatbot. This allows the chatbot to offer immediate and practical actions that the user can take.

Additionally, while focusing on "what's strong" offers a seemingly effective approach to hands-on community development, focusing on strengths does not disregard solving problems but rather emphasizes that community's should come together with their collective strengths prioritizing their collective needs [14]. Additionally problems in neighbourhoods affect its residents. Research into US neighbourhoods of concentrated poverty [41] illustrate that crime, physical and mental health and lack of education among many other issues are significant to its local citizens. Therefore, when faced with a chatbot in which to discuss their neighbourhood, users will inevitably report problems in their area. In these cases, the chatbot should respond sensitively and, in furthering community engagement, connect the user with someone who can contribute to resolving the issue or provide potential solutions directly. Clark et al. [13] investigate what makes a good conversation for conversational agents. While their findings show that a human-agent conversation should be transactional, some attributes of the human-human conversation found are helpful in designing the responses for more sensitive queries for neighbourhood problems. Key takeaways in designing the voice in these scenarios are *Mutual understanding and common ground* and *active listenership* [13]. These elements are significant for designing a chatbot that not only solves problems but responds appropriately to sensitive issues. Research shows that elderly can find companionship [39, 34] in chatbots and confide personal problems due to chatbot's sense of non judgemental listening. Additionally, providing users with factual information and resources helps mitigate feelings of isolation [**?**]. Given loneliness' relation to community problems, and the sensitivity around this problem, a specific knowledge base with factual data around this issue should be used to engage *active listenership.*

To engage community action members must be informed on the resources and steps available to them [9]. Research indicates that users often seek accurate and reliable information from chatbots, making it essential for these systems to be prepared to respond informatively to various queries [2]. For these information intention queries, the chatbot should provide reliable responses and adopt an informative tone ensuring users receive relevant information to address their prompt. When designing the informative aspect of the chatbot, insights from literature on customer service conversational agents [20] are valuable. This research suggests the importance of the chatbot accurately representing its capabilities and adapting its message length and complexity based on the situation. Therefore a knowledge base can be utilised by the chatbot that denotes its capabilities. Additionally, given that the chatbot's purpose is to tackle community disconnection, it must be prepared to offer relevant and specific information on this issue when prompted. Therefore the chatbot should have a separate knowledge base to provide facts about community disconnection, similar to how it addresses capabilities and loneliness intention prompts.

Overall, the chatbot should prompt users to action, to share their skills and offer immediate, practical actions, fostering community initiatives and empowerment. It should address neighbourhood problems appropriately, with the option of connecting users to ideal helpful neighbours. Additionally, the chatbot must provide accurate information and maintain a knowledge base on its capabilities, community disconnection and loneliness. These design elements ensure the chatbot effectively enhances community connectedness and engagement.

2.2.2 Implementation choices

Exploring the effectiveness of end-to-end learning models reveals both their potential and limitations in various applications. Bordes et al. [22], make a case for goal-oriented end-to-end learning models, which learn to provide feedback directly from training data. However, while the methods described are effective for tasks within well-defined domains such as restaurant booking, they may not be suitable for the broader context of community engagement as they require large amounts of domain-specific training data to perform well; this can be a limitation in the topic of community as new queries can frequently come up. Additionally, the chatbot this paper aims to implement has a range of tasks: it is task-based, informative and conversational [8]; the chatbot must guide users into action initiatives and potentially match users with other members of the neighbourhood; provide detailed and insightful answers; and adjust its tone and sensitivity in different contexts. Therefore, instead of relying solely on an end-to-end approach, incorporating a range of Natural

Language Processing (NLP) techniques is most appropriate.

To prompt users for skills and guide them into action-taking conversation flows, various frameworks can be implemented. Google's Dialogflow and Microsoft's Bot Framework offer powerful tools for building conversational agents [42, 23], but they are proprietary platforms, limiting customization and control. In contrast, the open-source Rasa [44] framework provides flexibility and control. Rasa's tools like rules and stories allow for customization of conversation paths based on user intents, ensuring that the chatbot can effectively guide users through tailored action-taking flows. Rasa also allows for separate action scripts - making it an appropriate base model for the chatbot's complex system - and buttons - making user input more direct for some prompts. Moreover, Rasa's user intent classification abilities are crucial for accurately understanding user inputs. This makes Rasa the most suitable choice for implementing a chatbot designed to enhance community connectedness and engagement, as it combines the benefits of open-source flexibility with effective conversational management features.

From the design choices review, the chatbot should be able to handle various user intents such as action_intent, problem_intent, information_intent, skill_intent, capabilities_intent, loneliness_intent, and disconnection_intent. Additionally, it should include generalised intents like general_action_intent ("I want to take action") and general_problem_intent ("I want to report a problem"), along with other trivial intents such as positive, negative, and greet. While there is no readily available data specifically for our chatbot domain, intent data can be generated by following guidelines set out by Rasa [6]. Taking inspiration from local government websites such as Cheshire East, UK, [15] and the Carlisle City Council Open Data Platform [1], potential user intents and variations can be formed and inputted into Rasa's DIET Intent Classifier [7]. By analysing the information provided on these platforms, we can create realistic and relevant intents to train the chatbot effectively. Additionally, further additions to the intent training corpus can be made by utilising a pilot study before the main study.

Given that we have a set of immediate actions configured from the design review: "Start a fundraiser," "Start a petition," "Start/join a group," "Start a solo/freelance venture," "Start an event," "Share a story," and "Seek further expertise" - these options outline a multi-class classification problem based on a user problem (with action), action, or skill prompt. To address this, models that capture the semantics of language are crucial. Transformers, such as BERT (Bidirectional Encoder Representations from Transformers), are highly effective for this purpose. BERT has demonstrated a high performance in understanding the semantics and nuances of language, significantly improving performance in text classification tasks [43]. BERT considers the context of words in a sentence bidirectionally, which allows for more accurate language classification [36]. Furthermore, BERT's implementation as an open-source model makes it accessible. This approach will generate accurate actions for the user prompt.

To provide accurate responses and advice to user prompts, these actions, along with the user prompt, should be fed into a large language model (LLM). Fine Tuning a LLM can be computationally expensive and beyond the capabilities of this research, in addition the inference of these models is also computationally expensive. Research has shown that quantization techniques can significantly reduce the computational requirements of LLMs while maintaining their performance [17]. Additionally, using a quantized version of LLaMA 2 7B [45, 5], known for its robustness in

NLP tasks, is both computationally efficient and effective. This model paired with a comprehensive systems message and the predetermined actions can deliver accurate and practical responses. This method allows us to achieve the desired functionality, generating helpful community initiatives to prompts, without the extensive resources typically required for fine tuning larger models. Furthermore, from the design review, it was decided that the chatbot should be prepared to provide less practical and more informative prompts as well as respond appropriately and with sensitivity to problems. In these cases, the same model (LLaMA 2 7B Quantised) can be utilised with alternative systems messages. For user prompts around capabilities, loneliness and disconnection a separate knowledge base, as decided in design review, should also be fed into the model along with the user prompt and specific systems message.

After problems have been reported users need to be able to search for these problems based on their skills and interests; therefore, problems must be searchable based on their similarity to the skill or interest. Research into Word2Vec [?] introduced converting textual data into vector embeddings, enabling systems to get an understanding of context and semantics and therefore able to compare the similarity between embeddings. Since our user prompts are sentences, Hugging Face's 'sentence-transformers/all-MiniLM-L6-v2' [38] model is optimised for producing sentence embeddings, and allows for more precise and efficient similarity searches. The chatbot can therefore utilise this method to store a user's problem in an unstructured dataset and then prompt another user to do a similarity search by running what the user that wants to take action states against the unstructured problems database. Among the available systems for managing such vector databases, Milvus [49] stands out as a suitable choice as it offers fast vector similarity searches and is open source.

2.2.3 Summary

Design	**Implementation**
Prompt users to share their skills and to take action	Utilise Rasa framework: rules, intents, and stories. Guide users into action-taking conversation flows and ask them to provide skills or interests. Rasa also serves as the base for other methods and actions.
Provide practical and immediate advice toward community initiatives	BERT multi-class classifier (Target classes: "Start/join a group," "Start a solo/freelance venture," "Start an event," "Share a story," and "Seek further expertise") fed, with user prompt, into LLaMA 2 7B-GPTQ model with a comprehensive systems message.
Deliver detailed and insightful answers to information queries and appropriate responses to more sensitive problem prompts	Utilise LLaMA 2 7B-GPTQ model with specific systems messages and knowledge bases for loneliness, information on disconnection, and chatbot capabilities intents.
Link user problems to ideal fellow neighbors	Store users' reported problems as vector embeddings (using 'sentence-transformers/all-MiniLM-L6-v2' model) in an unstructured database by Milvus. Perform similarity searches using users' skills to match with these problems.

Table 1: Design and implementation overview

3 NeighbourhoodBot implementation

Following the design and implementation review, Section 2.2, we present the following implementation for NeighbourhoodBot.

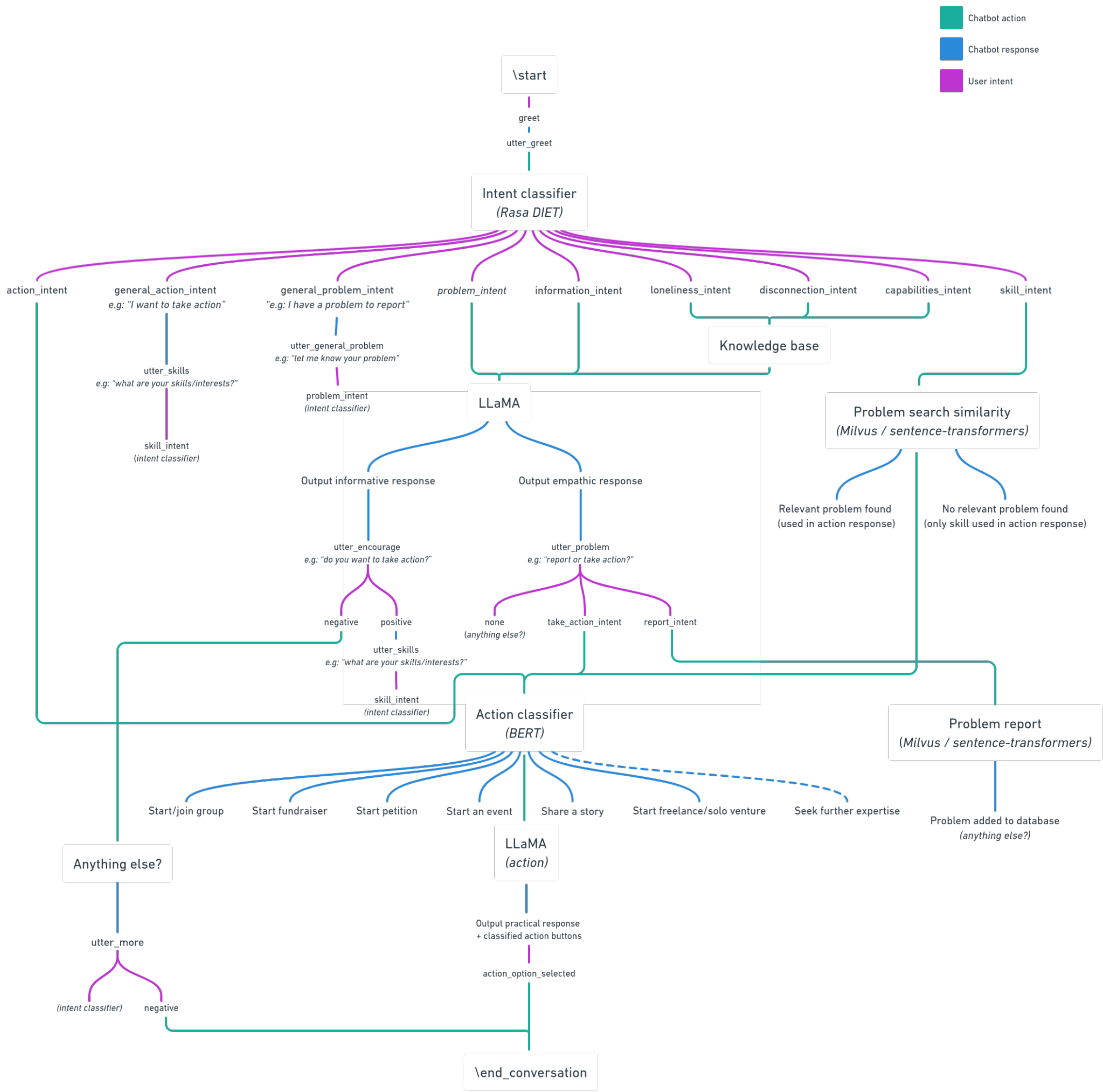

Figure 1: NeighbourhoodBot implementation flow.

4 Methodology

This methodology involves carrying out a pilot study to refine the design and implementation choices from Section 2.2, and executing a user study to test the refined choices. The user study aims to evaluate the NeighbourhoodBot's effects on participants and the potential impacts on a neighbourhood.

4.1 Pilot study

The primary objective of this pilot study was to address the first research question (RQ1), examining the effectiveness of our design and implementation choices in accurately responding to user prompts. This approach allowed the identification and improvement of any shortcomings in the NeighbourhoodBot's performance before proceeding to the user research study.

This experiment involved six participants who were freely able to communicate with the NeighbourhoodBot via Telegram, due to Telgram's API support made available by Botfather [4]. The evaluation metrics focused on the misclassification of user intents, categorising them as either within scope (reflecting implementation choices) or out of scope (reflecting design choices). After analysing the user prompts that lead to intent misclassifications and out-of-scope queries, we will use this analysis to enhance the intent training data and refine the design choices. This will broaden the scope and improve implementation accuracy before proceeding with the user study.

The participants received the following instructions before interacting with NeighbourhoodBot outlining the purpose of study, duration, how to participate, assumptions the chatbot has, data disclaimer, technical guidance, future context in regards to main study and when to provide feedback:

"' **Pilot study participation information**

Purpose: This pilot study is part of Orlando Closs' Bachelor's thesis in Artificial Intelligence aimed at enhancing a chatbot designed for discussing neighbourhood queries and enhancing community engagement. Your interactions will help improve the bot's response and adaptability for a larger main research study. This pilot study is looking at how you phrase your queries, what conversation paths you decide to take, and if the chatbot answers adaquatly.

Duration: The study will conclude on Sunday at 8pm CEST. You are encouraged to engage in up to three conversations, indicated by conversation_count/3. You may exceed this recommendation, but please be mindful of server limitations.

How to participate: You must install telegram. Start Conversations: Initiate each session with "Hi." Only send one message at a time and wait for the chatbots response. If pressing a button, only press once. End Conversations: A session ends either when you select an action or no further assistance is required, marked by "Conversation ended conversation_count/3."

Assumption: The chatbot acts under the assumption that it is connected to a digital platform where you can share posts, petitions, fundraisers, events, and create groups with your neighbourhood.

Data collection: All conversations, along with your Telegram username, will be stored and reviewed for research purposes.

Technical guidance: Misrecognitions by the bot are part of the data collection process, and will help to improve the bot for the main research study. Responses may take up to 3 minutes for more complex queries.

Future context in main study: The main study will utilize character cards to guide interactions, e.g., a participant might use a profile like "James Smith, a 34-year-old retail manager interested in cycling and gardening, facing neighborhood issues like vandalism and noise." In this pilot study you do not have these constraints, but let this be inspiration.

Feedback: Please report any technical issues or practical errors encountered during interactions to enhance system troubleshooting.

Thank you for your participation and valuable contributions to this research project. "'

Quote 1: Instructions provided to participants for the pilot study.

4.2 User study

The user research experiment is designed to simulate community interactions in order assess the efficacy of the design and implementation choices in creating a chatbot for community connectedness/engagement (RQ1), answer to if chatbots that focus on community development increase users sense of responsibility, care and contributions to their local neighbourhood (RQ2), and to assess whether a chatbot that store and relay users' requests for assistance can effectively faciliate connection between individuals seeking help and those willing to provide it (RQ3).

4.2.1 Interaction

This experiment creates an environment in which 19 participants in the role of fictional characters of a fictional neighbourhood interact with the NeighbourhoodBot. These characters, made to reflect members of an urban neighbourhood, are designed with the proportional statistics from 2019 Census (London) [24] in mind, detailed in the appendix. To avoid potential stereotypes, racial characteristics were intentionally excluded when designing the character profiles, focusing instead on skills and traits, occupation, age and household. Prior to the experiment, problems were loaded into the system's vector database with ideal candidates predetermined; this helps to later evaluate the NeighbourhoodBot's effectiveness in identifying and matching local residents to the problems, addressing the third research question (RQ3).

Tom Wilson

Age: 50

Occupation: Construction manager

Skills/interests: Visiting historical sites / amateur historian, woodworking, Father of three, including one early-years child.

Potential problems: Construction noise, safety concerns with nearby building projects

Quote 2: Example character profile for main research study.

Participants talk to the chatbot through Telegram due to its accessibility and API support provided by Telegram's *Botfather* [4]. Each participant is required to engage authentically, to the best of their ability, in the role outlined on their character card across three distinct conversations.

A conversation starts with the chatbot's initial greeting and ends with either an action, or no further assistance required. Prior to the experiment, participants are informed about data collection and their role in the experiment. A disclaimer ensures that all participants are aware that their interactions, while based on fictional scenarios, will be analysed for research purposes.

> **User Study Chatbot Interaction Information**
>
> **Purpose:** This user study involves interacting with the NeighbourhoodBot via telegram. Your conversations will be used to assess how chatbots can engage users into community action and link ideal neighbourhood problems to their skill sets and interests.
>
> **How to Participate:** You must install telegram. Please interact with the chatbot in the role of your character card (see next messsage). If prompted for skills or interests please stick to the character card guidance. Otherwise feel free to use the chatbot as you wish somewhat constrained within this role. Prompts include requesting neighbourhood information, reporting problems or working towards community initiatives in the neighbourhood. Start Conversations: Initiate each session with "Hi." Only send one message at a time and wait for the chatbots response. If pressing a button, only press once. End Conversations: A session ends either when you select an action or no further assistance is required, marked by "Conversation ended conversation_count/3." Please engage in three conversations (you may do more if you wish).
>
> **Assumption:** The chatbot acts under the assumption that it is connected to a digital platform where you can share posts, petitions, fundraisers, events, and create groups with your neighbourhood.
>
> **Data Collection:** All conversations, along with your Telegram username, will be stored and reviewed for research purposes.
>
> **Technical Guidance:** Responses may take up to 3 minutes for more complex queries. Please let me know if you believe you are experiencing any technical errors.
>
> Thank you for your participation and valuable contributions to this research project.

Quote 3: Instructions provided to participants for the main study (interacting with NeighbourhoodBot).

4.2.2 Questionnaire

Participants complete a questionnaire before and after interacting with the NeighbourhoodBot to evaluate changes in their perceptions of community involvement. This questionnaire, inspired by Sense of Community Index 2 (SCI-2) [11], assesses the participants' sense of responsibility, care, and contributions (RQ2) as well as whether their needs are likely to be met (RQ3) within their neighbourhood. Responses will be collected on a scale from 0 (Not likely) to 3 (Completely likely) for a series of statements. In each questionnaire there are 16 statements with 4 statements each belonging to the categories assessing local resident needs (RQ3), care (RQ2), responsibility (RQ2) and contributions (RQ2). For each statement in the *before* questionnaire, it directly corresponds to a statement in the *after* questionnaire with the addition of "With access to the NeighbourhoodBot, (..)" (see appendix B); therefore we can make a direct comparison of questionnaire scores.

4.2.3 Evaluation

To evaluate the outcomes, we focus on the following measures: the misclassifications of user intents and out of scope prompts (RQ1); the ability of the NeighbourhoodBot to correctly match problems with predetermined ideal candidates (RQ3); the results to the questionnaire and difference in scores between before and after (RQ2, RQ3); the number and distribution of actions selected across conversations (RQ2); and general observations of the conversation flows (RQ1, RQ2, RQ3).

5 Results

5.1 Pilot study: intent classification accuracy

In the pilot study, we analyse the incorrect classification of user prompts in order to improve the chatbot for the user study. In the table below we comment on the misclassifications to inform the future improvements.

#	**Prompt**	**Classified**	**True**	**Comments**
1	What sort of problems are people having	general_problem_intent	general_action_intent	While the user here is requesting information, the bot fails to classify the semantics of the message and recognises similarity to general problem intents such as "I want to report a problem in my area". This prompt and variations should be added to the general_action_intent training data as the person is interested in the issues of its area and whats to search the problems database.
2	I hear my neighbors fighting and screaming at night. What can I do about it? The police didn't do anything	information_intent	problem_intent	The user is stating a problem they are facing in their neighbourhood and asking for action, yet the use of language "What can I do" makes the bot recognise this intent as an information request which uses similar language in its training corpus such as "What platforms can I use to discuss community issues?" The intent data for problem_intent must be improved using this prompt and variations.
3	Software development	information_intent	skill_intent	Skill intent training data dominated by phrases such as "I like software engineering" or "I am skilled at software engineering" must account for users going straight to the action as skill is often prompted by the chatbot.
4	Should I contact local authorities for approval?	action_intent	OUT OF SCOPE	While giving a generic reply to this message is within the capabilities of the chatbot, the user is referring to a previous message. The bot does not have context of the conversation and only stores information in which it can offer practical advice on: skills, actions, problems.

5	Can you please generate me an email template that I would send to the council overseeing the area where I would try to establish my project?	general_problem_intent	OUT OF SCOPE	The chatbot is not setup up to create templates.
6	What is going on in my community at the moment?	disconnection_intent	OUT OF SCOPE	The chatbot holds no information about a specific community, this is an interesting idea for further improvements.
7	I have created a community garden, to mobilize and bring people together in my neighborhood. However recently a group of teenagers have vandalized the garden multiple times. This leaves us with monetary troubles while also bringing down morale. Do you have any suggestions how to handle the situation?	problem_intent	action_intent	While the user highlights problems, they ask for suggestions to actions; must distinguish better between these two intents in training data, using this prompt and variations.
8	Should I try to discuss the issue with the perpetrators first, or should I go to the police?	general_problem_intent	OUT OF SCOPE	This prompt is out of scope as the chatbot does not have memory in storing context.
9	Should I try to have a discussion with the teens that are causing the trouble or should I call the police?	general_problem_intent	OUT OF SCOPE	Chatbot does not have memory of the context of the conversation.
10	I like the social media idea, I would like to create a unified graphical design for the garden, however I am not an illustrator, nor do I have the money to employ one. Do you have any recommendations how to overcome this issue?	general_problem_intent	action_intent	General problem intent wrongly classified even though not semantically close to this prompt. The user asks for help to take action; must add prompt and variations to action_intent training data.
11	hey chatbot how many people live on my road	information_intent	OUT OF SCOPE	The chatbot has no knowledge base referring to specific information of the community.
12	ah super useful thank you	action_default_fallback	OUT OF SCOPE	The user was expressing gratitude as their last message, a gratitude intent would be a helpful addition to the chatbpt.
13	hey chatbot what should i do if my neighbour keeps parking in front of my house	disconnection_intent	action_intent	The user is asking for helpful advice in taking action and this prompt, and variations, should be added to the training corpus for action_intent.
14	I have some extra money I want to invest in public education, can you guide me through some steps	general_action_intent	action_intent	The language "I want to" and "some steps" made the chatbot recognise this as the user wanting to take action in a general way; however, ignores the semantics which should have triggered action_intent. This prompt along with variations should be added to the training corpus of action_intent.

Table 2: NeighbourhoodBot errors in classifying and responding to user prompts in pilots study.

Out of 43 user input prompts (excluding trivial prompts like "yes"), the chatbot incorrectly classified 7 intents (16.3%) and an additional 7 intents (16.3%) were beyond the chatbot's capabilities, leading to inappropriate action selection or error messages.

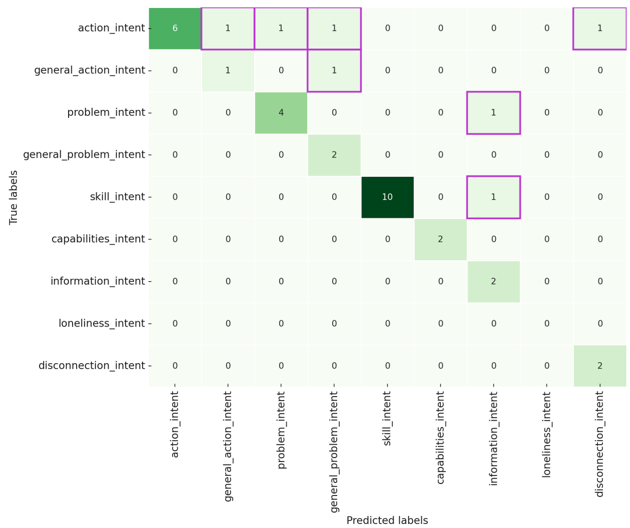

Figure 2: Confusion matrix to show correct and incorrect classifications by the NeighbourhoodBot in the pilot study: predicted against true values.

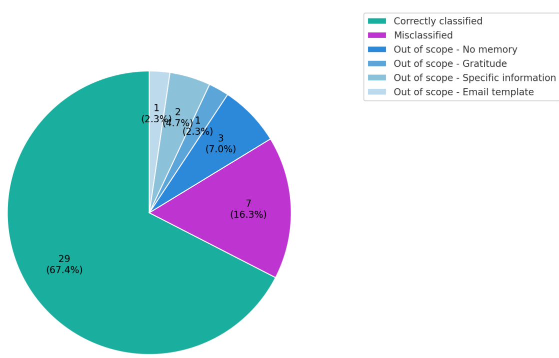

Figure 3: Pie chart to show proportion of correct classifications, incorrect classifications and out of scope prompts.

5.2 User study

5.2.1 Intent classification accuracy

The classification accuracy of non-trivial intents saw a notable improvement, increasing from 67.4% in the pilot study to 87.4% in the user study. This increase from the pilot to the user study in correct classifications is statistically significant, as validated by an independent two-proportion z-test with a 99.9% confidence level. There is also a notable reduction in out-of-scope user prompts—from 7 out of 43 in the pilot study to just 2 out of 95 in the user study.

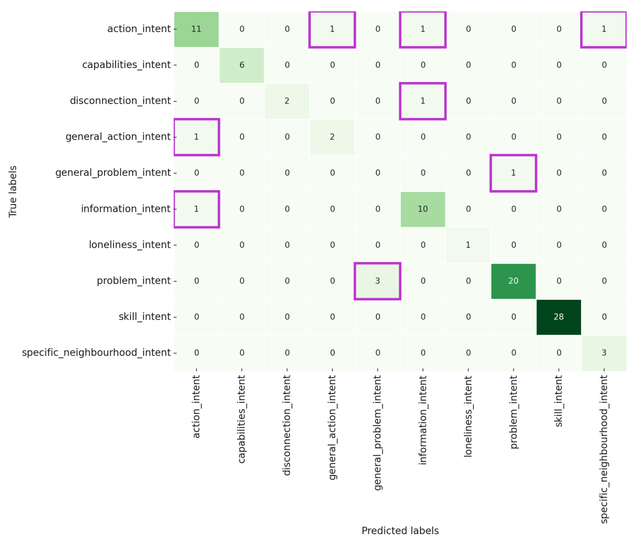

Figure 4: Confusion matrix to show correct and incorrect classifications by the NeighbourhoodBot in the user study: predicted against true values.

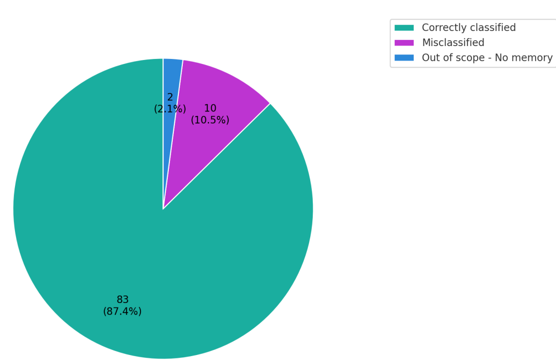

Figure 5: Pie chart to show proportion of correct classifications and incorrect classifications.

5.2.2 Selected actions

Out of 68 conversations, 31 concluded with users choosing a specific action.

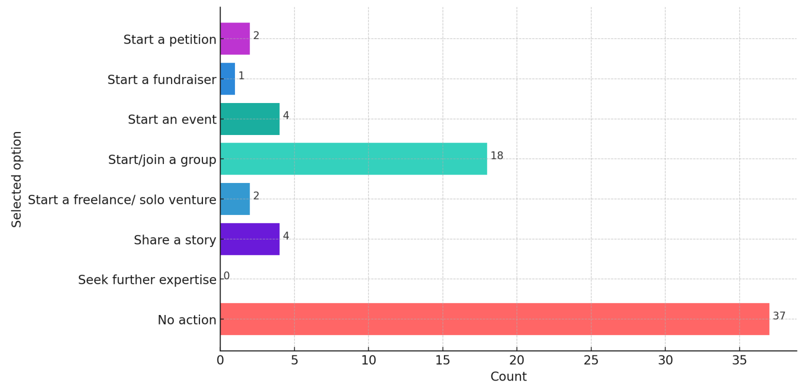

Figure 6: Bar chart to show actions selected to end the conversation across the 68 conversations made in the research study.

5.2.3 Questionnaire

The questionnaire analysis, supported by a paired t-test with a 99.9% confidence interval, indicated significant increases in users' sense of responsibility, care, contributions, and the likelihood of their needs being met by their neighbourhood after interacting with the chatbot.

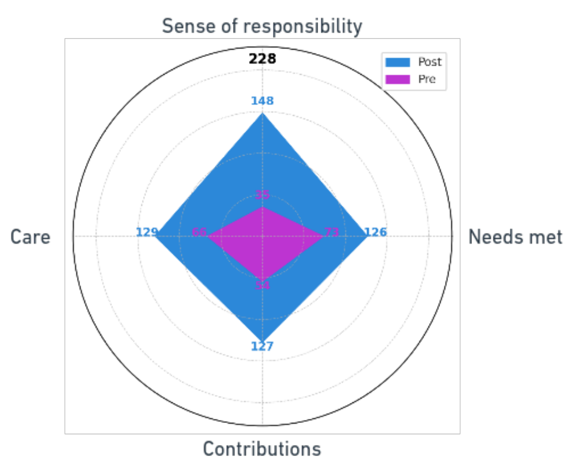

Figure 7: Radar chart to show questionnaire results across the four categories; showing differences in pre and post chatbot questionnaire scores.

5.2.4 Problem candidates

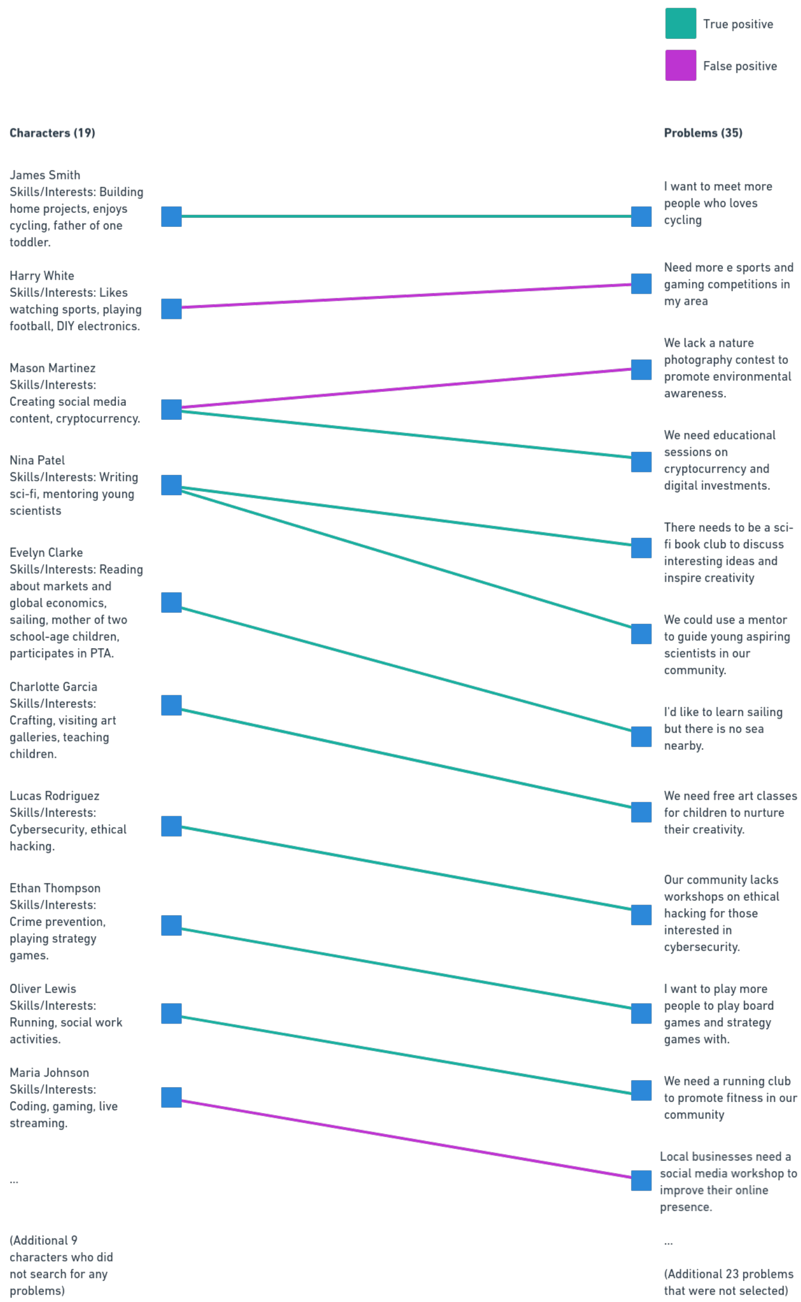

Figure 8: Visual to show characters (with skills/interests) who searched for problems to solve through the NeighbourhoodBot and whether they were the ideal match, or not.

In connecting community members based on their skills and needs, out of 19 participants, NeighbourhoodBot facilitated 12 connections for 10 characters. This process yielded nine accurate connections (true positives; predetermined ideal candidates) and showcased a few semantic misunderstandings (three false positives), such as confusing 'sports' with 'e-sports.'

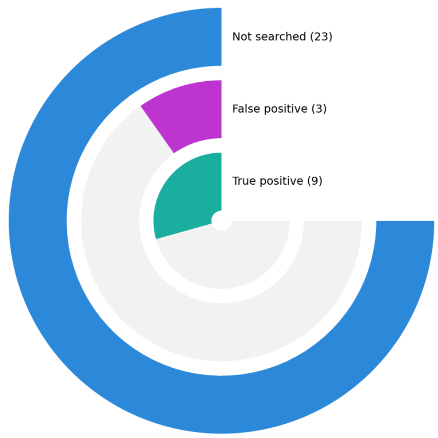

Figure 9: Radial bar chart to show the number of problems that were true positives (problems searched that were predetermined as ideal for a character), false positives (searched problem but not predetermined) or not searched for at all.

6 Discussion

6.1 Pilot study result analysis and improvements *(Section 5.1)*

A significant proportion of out-of-scope intents stemmed from the chatbot's inability to provide specific neighbourhood information, such as "What day are there markets in my neighbourhood?" or from its lack of conversational context memory. The chatbot does not retain memory and only stores specific intents (action_intent, skill_intent, and problem_intent) to inform subsequent actions. Other out-of-scope intents included requests for an email template or expressions of gratitude.

To improve the accuracy of classifications for the main research study and within the chatbot's scope, NeighbourhoodBot should be retrained using the pilot study's user prompts as part of the intent training corpus. A common issue with the Rasa's default DIET intent classifier [7] is its occasional failure to recognize the semantics of prompts due to limited contextual understanding; which is evident in the misclassifications in this pilot study (see Table 2). In contrast, LLMs like

GPT-3 have demonstrated significant results in natural language processing (NLP) benchmarks, including intent classification [37]. These models can interpret the semantics of user inputs more effectively, leading to more accurate intent recognition. Moreover, LLMs allow for the inclusion of intent definitions alongside data examples, enhancing the model's ability to understand and classify intents accurately. Davinci-002, a precursor to GPT-3, offers a computationally efficient alternative; despite its proprietary nature and the cost associated with OpenAI's API, Davinci-002 integrates with Rasa and is cost-effective. This integration can significantly enhance the NeighbourhoodBot's performance, reducing misclassifications.

Addressing out-of-scope intents poses a challenge. Implementing context memory is computationally intensive and beyond the current scope, as displayed as a hurdle in the development of educational chatbots [27]. For specific neighbourhood information, although beneficial for real-world applications, within this research's scope involving a fictional neighbourhood, the chatbot should refer such prompts to a conversational path similar to capabilities_intent. This would involve explaining why the chatbot cannot provide specific information; using LLaMA, alongside a capabilities knowledge base, to generate a relevant response. For gratitude intents, the chatbot should respond appropriately, e.g: "You're welcome, anything else?". For other unrecognised intents, such as requesting an email template, the chatbot should respond with an inability to fulfill the request and suggest asking for something else.

Following the pilot study, the chatbot is capable of appropriately responding to gratitude_intent, specific_neighborhood_intent, and other out-of-scope intents. Its intent training data is further enhanced using a more robust classification technique with the LLM Davinci-002. By addressing these key areas, NeighbourhoodBot improves its accuracy and user satisfaction for the user study.

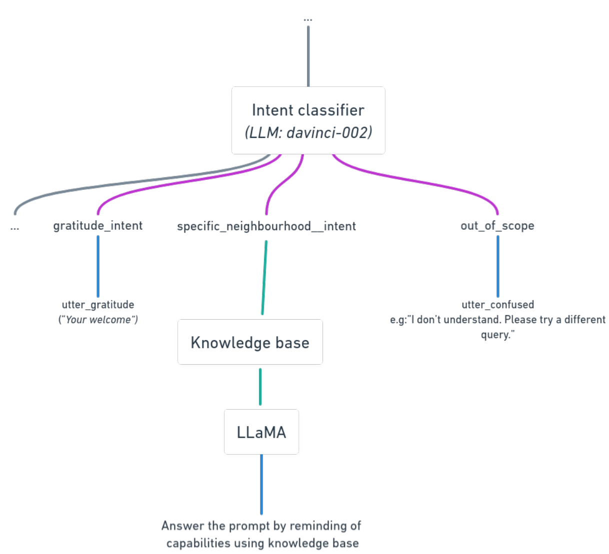

Figure 10: Additions to NeighbourhoodBot implementation (flow).

6.2 User study result analysis

6.2.1 Intent classification accuracy *(Section 5.2.1)*

The substantial reduction in out of scope prompts and statistically significant increase in correct classification demonstrates that NeighbourhoodBot now covers a broader array of user intents, and has effective scope for a chatbot designed at enhancing and engaging community connectedness, addressing Research Question 1 (RQ1).

Moreover, even when misclassifications occurred, the chatbot generally guided users towards constructive conversations and gave appropriate responses. When action_intent was mistaken for information_intent, for example, the user got less practical advice then what they were prompted for but were immediately prompted into an action taking path. Additionally when problem_intent was mistaken for general_problem_intent the user would be prompted for their problem again in which they responded by rephrasing (see Figure 11). The only completely inappropriate response found in the user study was when action_intent was mistaken for specific_neighbourhood_intent which resulted in an answer around the chatbot's capabilities instead of practical advice to the user's query.

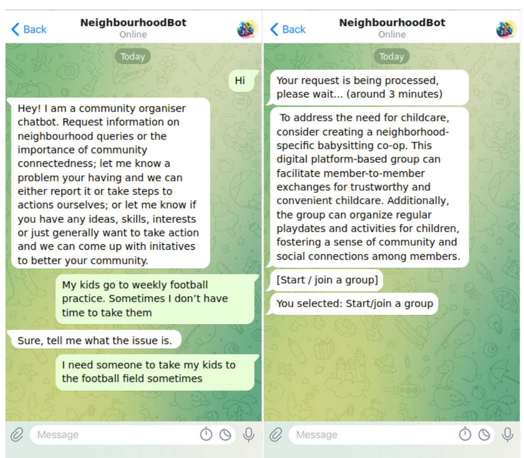

Figure 11: (Recreated) Screenshots of NeighbourhoodBot user study conversation. Example of mistaking problem_intent for general_problem_intent; resulting in chatbot prompting user for the problem.

6.2.2 Selected actions *(Section 5.2.2)*

Analysis of conversational outcomes showed that 31 conversations concluded with users choosing a specific action, which often involved starting or joining a community group. This choice was particularly prevalent, with 18 instances, suggesting that the chatbot effectively motivates users towards community-oriented actions. These results support the assertion that chatbots can enhance user engagement and foster a sense of responsibility and contribution within the community, directly addressing Research Question 2 (RQ2). It is important to note, however, these results come from a simulated setting with participants using fictional personas, which may affect their application to real-world situations (see *Limitations* Section 6.3).

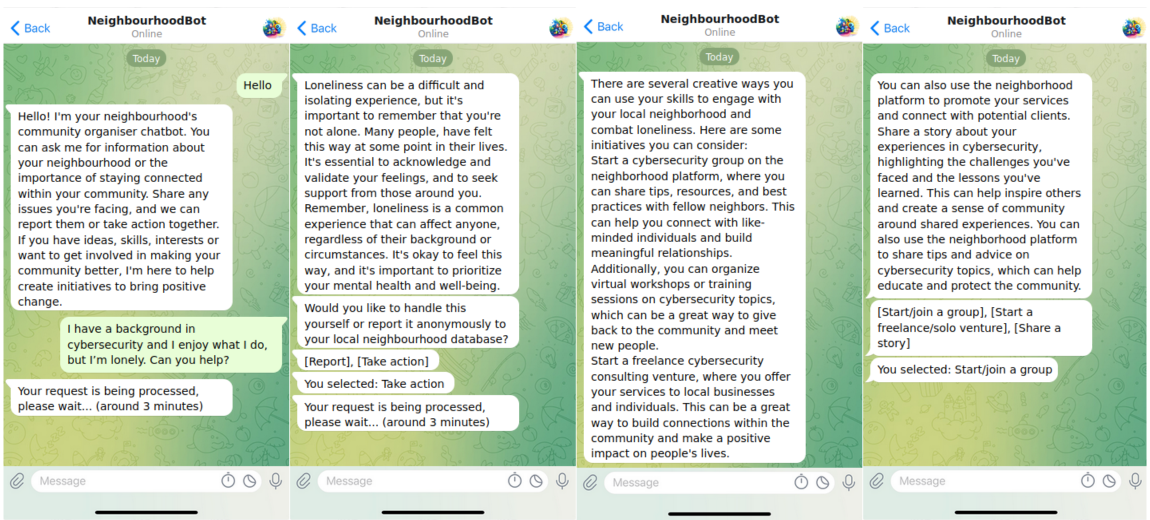

Figure 12: (Recreated) Screenshots of NeighbourhoodBot user study conversation. Example of conversation leading to selection of action based on the user's skills and problems.

6.2.3 Questionnaire *(Section 5.2.3)*

The area showing the greatest improvement was the sense of responsibility; this showed the lowest score in the pre-questionnaire and the highest score in the post-questionnaire. This suggests that the NeighbourhoodBot effectively empowers users, encouraging them to recognize their role and potential impact in their neighbourhoods with immediate and practical steps. The improvements in scores across all categories support the goals of increasing community engagement (sense of responsibility, care and contributions), as discussed in Research Question 2 (RQ2). The improved satisfaction with how community needs are met also touches upon Research Question 3 (RQ3).

6.2.4 Problem candidates *(Section 5.2.4)*

These results highlight the potential and current limitations of the chatbot in effectively matching community members' offers of help with requests for assistance, addressing Research Question 3 (RQ3). The participants that did not search for problems were not successfully guided into conversation flows where they inputted their skills in order to perform a similarity search, or a similarity search was performed but the language and semantics was not connected to an appropriate problem. Additionally, some participants inputted their skills within a larger prompt where they immediately asked for practical advice or were explaining a problem. The results suggest a promising direction for future improvements, particularly in enhancing the chatbot's semantic processing capabilities, to better understand and match user inputs (see *Future improvements* Section 6.4).

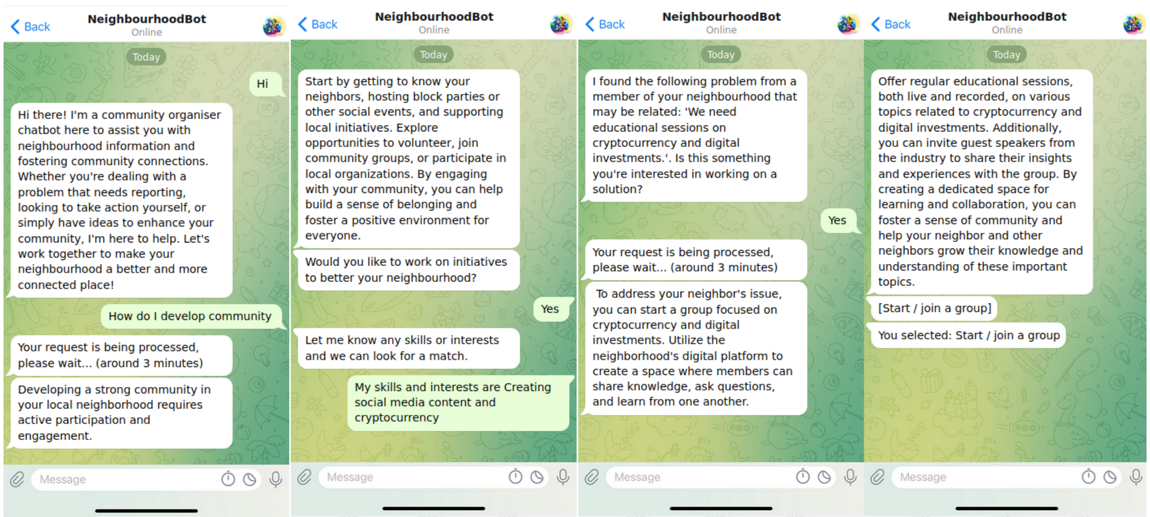

Figure 13: (Recreated) Screenshots of NeighbourhoodBot user study conversation. Example of conversation successfully matching a problem with an ideal candidate skill set.

6.3 Limitations

Despite the promising results, our study encountered several limitations that may have impacted the outcomes and should be considered when interpreting the findings.

6.3.1 No memory

The memory implementation in NeighbourhoodBot was restricted to storing only one prompt at a time for subsequent use in LLaMA, either for an action or problem query. This limitation arose due to constraints in computational resources and the complexities associated with implementing context awareness. Generally, this approach did not pose significant issues. However, challenges arose when some participants referenced previous messages, as the chatbot, lacking context awareness, failed to recognize or build upon these past interactions, limiting its response.

6.3.2 Selected actions metric

Participants were instructed to engage in three distinct conversations, concluding each by either declaring ”no more help necessary” or selecting a specific action while assuming the roles of assigned fictional characters. This experimental design introduces potential biases in the reliability of the action selection metric. The incentive to choose an action to progress in the experiment may have influenced participants' decisions, further influenced by the fact that these actions were hypothetical, with participants merely simulating responses on behalf of their fictional characters in a fictional neighbourhood. This setup could skew the authenticity of the action selection as a true metric of the NeighbourhoodBot's effect on community contributions.

6.3.3 Questionnaire

The participants of the questionnaire were predominantly aged between 18-24 and were students in London or Amsterdam. Consequently, when responding to the initial questionnaire, their answers were based on their experiences in their current neighbourhoods, where they neither owned homes nor likely felt a strong sense of community connectedness, resulting in low scores. In the second questionnaire, which included the prompt ”With access to the NeighbourhoodBot,” participants were able to consider a future sense of community, potentially leading to idealistic responses that may have skewed results in favour of the NeighbourhoodBot. Additionally, participants were instructed to assume that the neighbourhood was connected to a forum where they could share posts, petitions, fundraisers, and other community activities. This novel platform inherently carries value, possibly influencing participants to respond to the post-questionnaire with this broader context in mind, not just their interaction with the chatbot.

6.3.4 Ideal candidates

Problems were tailored to directly match the skills of each participant. In a real-world scenario, the language used would be less direct, necessitating more accurate embeddings to capture nuanced semantics. This discrepancy is a limitation of the experiment, as it does not perfectly replicate real-world conditions.

6.4 Future improvements

6.4.1 Real world scenario

The limitations encountered were largely due to testing the chatbot within a simulated environment. To enhance our analysis, we should deploy the chatbot in an actual neighbourhood, excluding fictional characters. Additionally, integrating a specialised knowledge base tailored to that neighbourhood will enable the chatbot to provide more precise information and address local community needs based on existing data about the area. Participants responding to surveys with real-life observations can offer insights on how the chatbot impacts their actual neighbourhood. This approach would also enhance the reliability of the selected actions metrics, as participants would need to actively want to engage in actions by clicking the buttons. Additionally, it would allow for more precise analysis of candidate connections by incorporating real-world problems.

6.4.2 Implementation

Based on the analysis and limitations, several potential improvements for the chatbot include developing a context-aware chatbot equipped with memory capabilities to enhance interaction continuity. Additionally, refining the chatbot's ability to accurately match problems with relevant skills through the use of a more advanced semantic sentence embedder could be beneficial. A more substantial transformation might involve adopting an end-to-end approach, requiring a vast corpus of fine-tuning data. While this method would demand significant data input, it would eliminate the need to predefine user intents, offering a more flexible interaction model. In transitioning to an end-to-end system, the chatbot could move away from a rigid rule-based system to a more dynamic framework.

7 Conclusion

NeighbourhoodBot leverages community development research to offer a potential solution to the prevalent issue of disconnection in Western urban environments. Through the exploration of neighbourhood-building literature, this research formulated a design plan that: prompts users to share their skills, provides practical and immediate advice on community initiatives, delivers detailed responses to information queries, and links users to ideally suited neighbours. After refining this design based on findings from a pilot study, the chatbot demonstrated a high accuracy in classifying user prompt intentions and faced minimal limitations, with only two out-of-scope prompts due to lack of context awareness.

To assess its effectiveness in enhancing users' sense of responsibility, care, and contributions to the local neighbourhood, a questionnaire revealed a significant increase in these factors across all categories, validating the chatbot's ability to boost citizen engagement. However, potential biases exist, as the study was not conducted in a real-world environment.

NeighbourhoodBot effectively facilitated connections between individuals seeking assistance and those willing to provide it. Although the implementation has shown promising results, it primarily serves as a starting point for further enhancements, particularly through the integration of more advanced semantic embedding models. This holds significant potential for future adaptations of conversational agents aimed at community connection goals.

This study contributes to the field of conversational agents, particularly in their application towards mental health, motivating action, and group organisation. It demonstrates the potential impacts that chatbots can have in achieving these objectives and suggests practical ways for their implementation. Additionally, this study highlights the integration of community development research with technology and software approaches, showing how digital tools can directly enable neighbourhoods to adopt these methods without requiring an intermediary. The problem of disconnection is often an overlooked area of innovation; this research offers a potential novel solution providing a system that speaks to individuals to address collective needs.

7252 words

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A Appendix: Census Data and Character Card Distribution

Table A1: Original London Census Data (2019) [24]

Category	Percentage	Number
Total Persons Aged 16-64	-	6,036,893
Total Persons Aged 65+	-	1,081,515
Median Age	-	35.6
16+ Unemployed	4.9%	-
Self-Employed	12.6%	-
Electricity, Gas, etc. Supply	0.2%	-
Water Supply and Waste Management	0.3%	-
Construction	3.8%	-
Wholesale and Retail Trade	11.5%	-
Transportation and Storage	4.9%	-
Accommodation and Food Services	8.1%	-
Information and Communication	8.4%	-
Financial and Insurance Activities	7.3%	-
Real Estate Activities	2.7%	-
Professional, Scientific and Technical Activities	12.9%	-
Administrative and Support Service Activities	10.8%	-
Public Administration and Defence	4.4%	-
Education	7.1%	-
Human Health and Social Work Activities	10%	-
Arts, Entertainment and Recreation	2.7%	-
Other Service Activities	2.3%	-
Households with at least 1 early-years or school age child	25.4%	888,561

Table A2: Representation in Character Cards

Category	Number of Characters (out of 20)	Percentage Representation
Electricity, Gas, etc. Supply	1	5%
Water Supply and Waste Management	1	5%
Construction	2	10%
Wholesale and Retail Trade	1	5%
Transportation and Storage	1	5%
Accommodation and Food Services	1	5%
Information and Communication	1	5%
Financial and Insurance Activities	1	5%
Real Estate Activities	1	5%
Professional, Scientific and Technical Activities	2	10%
Administrative and Support Service Activities	2	10%
Public Administration and Defence	1	5%
Education	2	10%
Human Health and Social Work Activities	2	10%
Arts, Entertainment and Recreation	1	5%
Self-Employed	2	10%
Households with at least 1 early-school age child	4	20%

B Appendix: Questionnaire

Table B3: Pre-Questionnaire

No.	Statement	Not likely	Somewhat likely	Mostly likely	Completely likely
1	I am likely to get important needs of mine met because I am part of my neighbourhood.				
2	If there is a problem in my neighbourhood, members are likely to get it solved.				
3	People in my neighbourhood are likely to respond promptly to community issues.				
4	It is likely that I can rely on community resources when I need help.				
5	I am likely to put a lot of time and effort into being part of my community.				
6	My neighbourhood is likely to influence other neighbourhoods.				
7	I am likely to have influence over what my neighbourhood is like.				
8	Being a leader in my community is likely to be important to me.				
9	In my current neighbourhood, I am likely to want to be part of the community.				
10	I am likely to be with other community members and enjoy being with them.				
11	I am likely to be part of my neighbourhood for a long time.				
12	Members of my neighbourhood are likely to have shared important events together.				
13	I am likely to think of initiatives for the sake of my local neighbourhood.				
14	Contributing to local community projects is something I am likely to do.				
15	I am likely to participate in my neighbourhood's decision-making processes.				
16	I feel my contributions can significantly impact my neighbourhood.				

Table B4: Post-Questionnaire

No.	Statement	Not likely	Somewhat likely	Mostly likely	Completely likely
1	With access to the NeighbourhoodBot, I am likely to get important needs of mine met because I am part of my neighbourhood.				
2	With access to the NeighbourhoodBot, if there is a problem in my neighbourhood, members are likely to get it solved.				
3	With access to the NeighbourhoodBot, people in my neighbourhood are likely to respond promptly to community issues.				
4	With access to the NeighbourhoodBot, it is likely that I can rely on community resources when I need help.				
5	With access to the NeighbourhoodBot, I am likely to put a lot of time and effort into being part of my community.				
6	With access to the NeighbourhoodBot, my neighbourhood is likely to influence other neighbourhoods.				
7	With access to the NeighbourhoodBot, I am likely to have influence over what my neighbourhood is like.				
8	With access to the NeighbourhoodBot, being a leader in my community is likely to be important to me.				
9	With access to the NeighbourhoodBot, I am likely to want to be part of the community.				
10	With access to the NeighbourhoodBot, I am likely to be with other community members and enjoy being with them.				
11	With access to the NeighbourhoodBot, I am likely to be part of my neighbourhood for a long time.				
12	With access to the NeighbourhoodBot, members of my neighbourhood are likely to share important events together.				
13	With access to the NeighbourhoodBot, I am likely to think of initiatives for the sake of my local neighbourhood.				
14	With access to the NeighbourhoodBot, contributing to local community projects is something I am likely to do.				
15	With access to the NeighbourhoodBot, I am likely to participate in my neighbourhood's decision-making processes.				
16	With access to the NeighbourhoodBot, I feel my contributions can significantly impact my neighbourhood.				

Respondents should rate each statement using the following scale:

- 0 - Not likely
- 1 - Somewhat likely
- 2 - Mostly likely
- 3 - Completely likely

The total community index is calculated by summing the scores from Q1 to Q16. The index is divided into four subscales:

- **Needs met:** Sum of Q1, Q2, Q3, Q4.
- **Sense of responsibility:** Sum of Q5, Q6, Q7, Q8.
- **Care:** Sum of Q9, Q10, Q11, Q12.
- **Contributions:** Sum of Q13, Q14, Q15, Q16.