# Utilization of artificial intelligence to analyze interview data from the FREIIA project.

Patrick Kakis Gabrielsen, Bjørn Gitle Hauge, Anna-Lena Kjøniksen

Department of Engineering, Østfold University College, Norway

## Abstract

The FREIIA project resulted in a high amount of interview data collected from stakeholders at 6 islands: Koster (Sweden), Groix (France), Ouessant (France), Hvaler (Norway), Schiermonnikoog (Netherlands), Bornholm (Denmark). Initially, the interviews were analyzed manually, which was very time-consuming. We therefore developed an artificial (AI)-assisted methos for analyzing the interview data. This new method enabled us to analyze high amounts of data in a short time, which did not only save time, but also enabled us to conduct the whole design thinking process within one week, thereby also reducing traveling.

## 1. Introduction

A hybrid qualitative-AI methodology was developed and tested to analyze interview data collected within the FREIIA (Facilitating Resilience Embracing Islands Innovation) project. The interview data from stakeholders at the first three islands (Hvaler, Norway; Schiermonnikoog, Netherlands; Bornholm, Denmark), were originally analyzed manually. This was a very time-consuming process. An AI-assisted analyses method was therefore developed and utilized on the 3 other islands (Koster, Sweden; Groix, France; Ouessant, France). To compare, the new method was also used on the first 3 islands. The utilization of AI-tools was used not only to accelerate qualitative data processing, but also to support multilingual analysis, and cross-regional comparison.

## 2. Methods

### 2.1 Process

On each island, interdisciplinary teams conducted semi-structured interviews with local stakeholders, including municipal planners, business owners, community leaders, and residents. The interviewed stakeholders were also invited to participate in a workshop, which was held at the end of each visit. For the first 3 islands, the interview data was manually analyzed. For the 4$^{th}$ island, AI-assisted text analysis was therefore developed and tested. This proved to be a success, and AI-assisted analyses were therefore employed on islands 5 and 6. In addition, the interview data from island 1-3 was re-analyzed utilizing the new AI-assisted method.

## 2.2 AI-analyzation design

The project followed a sequential design consisting of:

1. Qualitative data collection,
2. AI Custom GPT analysis,
3. Human validation,
4. Design thinking workshops.

**Phase1 Data input through Semi-Structured Interviews**

The interviews were recorded and converted into text format utilizing Nettskjema.no, which is developed by the University of Oslo University. This web-app uses Open AI's Whisper to convert audio into text and is approved for sensitive data. Nettskjema.no can also translate from the original interview language into another language. The interviews were transcribed into both English and to the original language. English was utilized for further processing of the interviews, while the original language was used to facilitate quality control of the translated statements.

**Phase 2 Creating the CustomGPT**

*Step 1. Format the data*

To ensure clarity and structure in the data processing phase, all interviews were compiled into a single text document in which each interview was explicitly marked using consistent framing phrases such as:

Start interview 1

(interview text)

End interview 1

This approach allowed the AI model to recognize the boundaries of each interview, making it possible to distinguish where one interview ended and the next began. Structuring the data in this way also enabled accurate attribution of quotes during the analysis process, significantly reducing the risk of hallucinations, where the AI might otherwise misattribute or invent content.

*Step 2. Creating and initiating ChatGPT session*

The ChatGPT session was made ready for data analysis:

- Create OpenAI account for ChatGPT, and upgrade to licensed version.
- Create Custom GPT
- Upload all relevant files.
- Disable Open AI's ability to use the information for future training.

- Ensure that the data and analysis is not available for anyone outside the project group.
- Add project name
- Add project description
- Add instructions based on the Automatic Framework.

**Phase 3  Prompt Engineering**

Prompting the CustomGPT with our farmwork and our data. Utilizing a range of different questions.

**Phase 4 Grounded Theory**

While ChatGPT is effective at general language tasks, high-quality thematic analysis requires prompt calibration and targeted instruction to align model outputs with qualitative research goals. This required considerable manual intervention and added to the cognitive and time burden of maintaining transparency and reproducibility. However, to utilize Grounded theory we had to be creative in how the CustomGPT gave us answers, and thus added the following instruction promt:

*“Use interview documents to provide answer, What interview is the gap from in Collom A, What gap is presented in Collum B, and what is the direct quote from the interview in Collum C.”*

The answer then had to be controlled and checked in the original transcript, to see if the quote matched the gap, and was pulled from the correct interview. The correct answer, with good useable gaps, was placed into a new document for use in Phase 5 (problem framing session).

This method made it easier and less work intensive to sort out hallucinations (when AI is making up answers).

**Phase 5 ”Human in the loop”**

During phase 5 we implemented “human in the loop” [1], a term also known as Human-AI collaboration. In this process the interplay between humans and AI plays an important role, instead of a process that is completely automated by AI. Both feedback from the project participants and results from previous studies [2], show that participant inclusion during the process is important for trust and ownership of the results. Without ownership of the problem statements, the probability of gaining successful outcomes from the Design Thinking Workshops is small. This becomes even more important after implementing AI-assisted analyses, since many people are distrustful of AI-generated content.

## 3. Results and discussion

The integration of Custom GPTs into the qualitative analysis process enabled the identification of key stakeholder challenges across three island communities, and in the last two islands in under two hours of model interaction. In total, 148 semi-structured interviews were processed, representing over 529,414 words of transcribed material in English, French, and Swedish, se details in Table 1 and Table 2. AI-supported analysis, combined with human validation, resulted in a set of five problem statements per island. These statements were used as the thematic foundation for subsequent co-creation workshops.

With the integration of Custom GPT, we were able to revise this blueprint, conducting both the interviews and the workshop within the same week, thereby reducing the need to travel to the destination more than once.

The utilization of AI during this process enabled us to:

- Analyze interviews from different countries without knowing the languages.
- Reduce analysis time from 150 days to 2 hours per island.
- Reduce the number of travels by 50 %, since the data can be analyzed on-site.
- Easily deal with vast amounts of data, thereby allowing us to perform more interviews.
- Identify innovation gaps used for the design thinking process.

Table 1. Overview of the number of interviews, pages, and words analyzed in the study.

| INTERVIEWS | | INTERVIEW STATISTICS | | |
|---|---|---|---|---|
| | | Interviews | Pages | Words |
| | Hvaler | 20 | 379 | 122 265 |
| | Schiermonikoog | 23 | 668 | 113 390 |
| | Bornholm | 17 | 124 | 70 909 |
| | Koster | 45 | 836 | 125 255 |
| | Groix | 13 | 101 | 38 729 |
| | Ouessant | 30 | 193 | 58 866 |
| | SUM | 148 | 2301 | 529 414 |

Table 2. Overview of participating students and stakeholders involved in the study.

| FREIIA PARTICIPANTS | | Hvaler | | Schiermonikoog | | Bornholm | | Koster | | Groix | | Ouessant | | Sum Participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | InnovationGap | Design Thinking | InnovationGap | Design Thinking | InnovationGap | Design Thinking | InnovationGap | Design Thinking | InnovationGap | Design Thinking | InnovationGap | Design Thinking | |
| Students | Norwegian | 21 | 49 | 12 | 15 | 12 | 12 | 18 | 17 | 15 | 15 | 15 | 15 | 216 |
| | Dutch | | | 10 | 4 | | | | | | | | | 14 |
| | Belgian | | 9 | | | | | | 19 | | | | | 28 |
| | Danish | | | | | 3 | 4 | | | | | | | 7 |
| | Swedish | | | | | | | 7 | 4 | | | | | 11 |
| | French | | | | | | | | | | | 2 | 2 | 4 |
| | **SUM** | 21 | 58 | 22 | 19 | 15 | 16 | 25 | 40 | 15 | 15 | 17 | 17 | |
| Total participating students | | | | | | | | | | | | | | 280 |
| Stakeholders | Norwegian | 20 | 20 | | | | | | | | | | | 40 |
| | Dutch | | | 23 | 9 | | | | | | | | | 32 |
| | Danish | | | | | 17 | 6 | | | | | | | 23 |
| | French | | | | | | | | | 13 | 4 | 30 | | 47 |
| | Swedish | | | | | | | 46 | 3 | | | | | 49 |
| Total participating stakeholders | | | | | | | | | | | | | | 191 |
| **TOTAL ACTORS** | | | | | | | | | | | | | | **471** |

### 3.1 Transparency, Documentation, and AI Limitations

While the integration of ChatGPT and generative AI significantly improved our analytical capacity, it also introduced several challenges, especially concerning transparency, reproducibility, and documentation. The nature of generative AI is highly fluid and conversational. During the analytical process, prompts are developed and adjusted continuously. When initial responses are insufficient or misaligned with the research objective, the process becomes iterative. Researchers must refine, rephrase, and repeat their prompts until the AI generates outputs that are analytically useful. This dynamic process is strongly influenced by the prompter's perspective and the intended purpose of the task.

This study demonstrates the potential of generative AI to transform qualitative research processes without compromising the interpretive depth that is foundational to the discipline. By embedding AI within a grounded and participatory research framework, we were able to rapidly analyze large volumes of multilingual data, support stakeholder-driven innovation processes, and enable real-time knowledge generation within fieldwork contexts.

The framework developed in this project introduces a principled approach to AI-augmented qualitative research that emphasizes three core dimensions:

1. Alignment with grounded theory and design thinking,
2. Use of prompt engineering and ethical constraints to guide AI behavior, and
3. A human-in-the-loop validation model to ensure quality, relevance, and accountability.

### Practical Implications

The integration of generative AI enabled us to compress the full research cycle, data collection, analysis, validation, and co-creation into a single week-long field deployment per island. This restructuring resulted in substantial savings in time, travel, and operational costs. More importantly, it allowed student researchers to participate in the full arc of inquiry, from stakeholder interviews to collaborative workshops. This continuous engagement improved both student learning outcomes and the relevance of workshop outputs.

By democratizing the analysis process, AI tools helped level the playing field among students with varying research experience. Participants who might have been less confident in manual coding were able to engage critically with GPT-generated insights, acting as reviewers and thematic synthesizers rather than starting from scratch. This aligns with constructivist learning models and suggests a broader role for generative AI in education and field-based training.

### Considerations and Risks

While generative AI offers powerful capabilities for qualitative research, it also presents unique risks. As others have noted, large language models are prone to hallucinations, overgeneralizations, and misinterpretation of culturally specific references. In our own work, we encountered these limitations, particularly when the AI was prompted to generate solutions or summaries without strict instruction. To mitigate this, we implemented source-tracing mechanisms, prompt discipline, and rigorous quote verification.

A further epistemic risk arises when researchers or participants accept AI outputs uncritically, particularly in areas where they lack domain knowledge. This "false fluency" effect underscores the importance of domain familiarity, critical engagement, and contextual validation in any AI-assisted qualitative workflow. Our team responded to this by requiring researchers to conduct background reviews on key topics before using AI to analyze related content. This pre-analysis preparation improved the ability to identify inaccuracies and maintain interpretive control.

### Toward Responsible Use of AI in Qualitative Research

The novelty of this work lies not only in its technical implementation but also in its contribution to the evolving standards for responsible AI use in qualitative inquiry. We argue that generative AI, when used transparently and ethically, can extend the reach of qualitative methods without undermining their foundational principles. However, this requires thoughtful integration not substitution of AI into each phase of the research process.

## 4. Conclusions

Utilizing artificial intelligence to analyze interview data in the scope of a design thinking process significantly reduces the time needed for analyzing the interviews. In addition, travel to the islands was reduced from 2 to 1 trips, since the interviews could be quickly processed on-site. However, it is important to establish good routines that ensures that AI-generated hallucinations are not contaminating the results.

### Future work

We are currently in the process of writing a scientific paper based on the work presented in this report.

### References


[1] L. Yan, V. Echeverria, G.M. Fernandez-Nieto, Y. Jin, Z. Swiecki, L. Zhao, D. Gašević, R. Martinez-Maldonado, Human-AI Collaboration in Thematic Analysis using ChatGPT: A User Study and Design Recommendations, Extended Abstracts of the CHI Conference on Human Factors in Computing Systems, (2024) 1-7. https://dx.doi.org/10.1145/3613905.3650732

[2] A.C. Edmondson, J.-F. Harvey, Extreme teaming: Lessons in complex, cross-sector leadership, Emerald Publishing Limited, 2017.