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Real-time assistance in suicide prevention helplines using a deep learning-based recommender system: A randomized controlled trial

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ABSTRACT

Objective: To evaluate the effectiveness and usability of an AI-assisted tool in providing real-time assistance to counselors during suicide prevention helpline conversations.
Methods: In this RCT, the intervention group used an AI-assisted tool, which generated suggestions based on sentence embeddings (i.e. BERT) from previous successful counseling sessions. Cosine similarity was used to present the top 5 chat situation to the counsellors. The control group did not have access to the tool (care as usual). Both groups completed a questionnaire assessing their self-efficacy at the end of each shift. Counselors' usage of the tool was evaluated by measuring frequency, duration and content of interactions.
Results: In total, 48 counselors participated in the experiment: 27 counselors in the experimental condition and 21 counselors in the control condition. Together they rated 188 shifts. No significant difference in self-efficacy was observed between the two groups ($p = 0.36$). However, counselors that used the AI-assisted tool had marginally lower response time and used the tool more often during conversations that had a longer duration. A deeper analysis of usage showed that the tool was frequently used in inappropriate situations, e.g. after the counselor had already provided a response to the help-seeker, defeating the purpose of the information. When the tool was employed appropriately (64 conversations), it provided usable information in 53 conversations (83%). However, counselors used the tool less frequently at optimal moments, indicating their potential lack of proficiency with using AI-assisted tools during helpline conversations or initial trust issues with the system.
Conclusion: The study demonstrates benefits and pitfalls of integrating AI-assisted tools in suicide prevention for improving counselor support. Despite the lack of significant impact on self-efficacy, the support tool provided usable suggestions and the frequent use during long conversations suggests counsellors may wish to use the tool in complex or challenging interactions.

1. Introduction

Online counseling for suicide prevention is a challenging profession with high turnover rates. This form of counseling can require a high cognitive load during conversations when counselors need to support individuals in need. However, obtaining help in a timely manner during these challenging situations is not always feasible.

Several studies have explored tools to assist counselors in their online work. Dinakar et al. [1] provided live topics through topic modeling. Salmi et al. [2] proposed a support tool that provided suggestions, which aligns with a proposed support tool framework by Madeira et al. [3]. The authors identified that a potential support tool would use natural language processing (NLP) to classify chat messages and then provide suggestions. Another approach was used by Demasi et al. [4], who proposed a retrieval-based chatbot that acts as a training partner for counselors.

This paper builds upon the work of Salmi et al. [2] by addressing its main limitations. [2] used a retrieval algorithm based on word embeddings and was evaluated on mock conversations. In this current study we built on this concept by applying deep learning to train a Transformer model on a large amount of helpline conversation data as a method to embed messages for retrieval. We aimed to create a tool that offers

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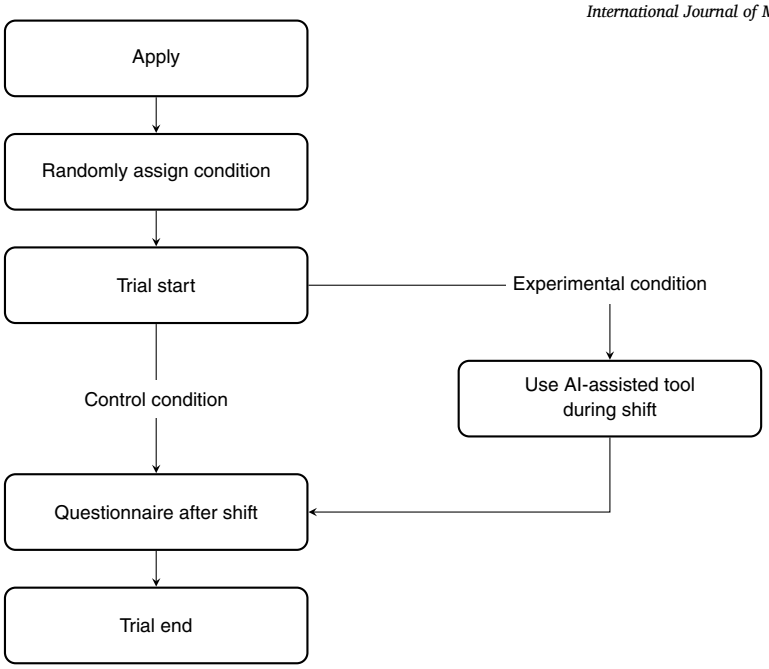

Fig. 1. Experiment design.

better embeddings and, thus, better suggestions, and implement it in real-time conversations. Through this method we hoped to address the main shortcoming of the work in [2]: the method of retrieval, and effectively boost counselors' confidence and enhance their ability to support people in distress.

With the emergence of transformers [5], the field of NLP witnessed a significant improvement in the methods for embedding text. In contrast to recurrent neural networks, transformers can maintain contextual information across the whole input range, while training is efficient. Through pre-training and fine-tuning deep networks, through methods like BERT [6], accurate and contextual word embeddings can easily be obtained.

Due to its complex nature, text retrieval in a suicide prevention setting is an ideal use case for transformer-based approaches. Methods like cross-encoders allow for effective sentence similarity but are slow in real-time use. If text is converted to a single embedding, it can be compared efficiently to a large database of embeddings through basic distance metrics, like the cosine distance. This approach has been shown to work well when comparing text embeddings [7] [8]. A popular method used in retrieval-based dialog systems is to combine these methods [9]. A top n number of documents are preselected as candidates using a less powerful but computationally less intensive method, like cosine similarity. Then afterward, the list of candidates is reranked using a more powerful but computationally more intensive method like cross-encoders [10].

For this approach it is important to have good sentence embeddings. A simple method to get an embedding for a sentence, or small piece of text, is to average word embeddings within a text. However, this method can only capture a limited selection of helpline cases. To be able to include as many helpline situations as possible, we therefore looked to more tailored methods. A prominent approach for sentence embedding is Sentence-BERT, introduced by Reimers et al. [8]. This method builds upon RoBERTa [11] by extending it to generate sentence embeddings. Sentence-BERT employs a Siamese RoBERTa network and is trained using triplet loss. The resulting embeddings can be efficiently compared using cosine similarity.

In this study, we trained a sentence embedder in the context of a chatservice of the suicide prevention helpline in the Netherlands with on average 500 calls per day. Furthermore, we evaluated this tool in a RCT, with the primary goal of observing the impact on counselors' self-efficacy after a shift. A secondary goal was to evaluate the tool's usage by comparing the provided suggestions with the resulting helpline conversations. To the best of our knowledge, this study is one of the first applications of an AI-assisted tool that provides automated tailored conversation suggestions in a real-time setting.

2. Methods

2.1. Study design

This study was designed as a randomized controlled trial. Counselors were randomly assigned to a control or intervention group. The intervention group was granted access to the AI-assisted tool during their shifts, while the control group did not have access to it (care as usual). At the end of each of 10 shifts, both groups were asked to fill in a four-item questionnaire. Fig. 1 describes the workflow of the study design. Furthermore, the usage of the AI-assisted tool during chat conversations was monitored.

2.2. Participants

Participants were recruited from 113 Suicide Prevention in the Netherlands. Initially, counselors were recruited through a questionnaire, where they could provide a code of their own choosing. To remain anonymous, a personal code was used to access the AI-assisted tool and complete the self-efficacy questionnaires. After the recruitment period of one month, the participating counselors were randomized, accounting for gender and age. A power analysis estimated 74 participants, with 37 participants per condition, for a maximum of 10 shifts. Due to a low response rate, we deviated from the initial recruitment method and selected another recruitment method for a period of two weeks. A randomized list of unique codes was generated to ensure participant anonymity, with a predetermined allocation to each condition. Counselors were asked to participate in this research during daily meetings at the start of their shifts. A helpline manager sequentially assigned participating counselors based on this randomized list. Counselors used the provided code from the list to access the AI-assisted tool and complete the questionnaires.

Table 1
Label definitions.

Label	Options	Definition
Usage	Adopted	One of the five suggestions was adopted or copied.
	Elements	Elements of one or more of the five suggestions were used.
	Disregarded	None of the five suggestions were used.
Usability	True/False	There was useable information among the five suggestions.
Incorrect usage	Early	The help seeker wrote a message after the tool was queried but before the counselor could answer.
	Late	The counselor wrote a reaction to the help seeker and queried the tool afterward.
	Double	The counselor queried twice without change in the conversation.
Incorrect situation	Begin	The counselor queried the tool at the beginning of the conversation or right after it was transferred to them.
	End	The counselor queried the tool at the very end of the conversation.

2.3. Measurements

2.3.1. Primary outcome measure

Using a Likert scale ranging from 1 to 10, participants were asked to rate their responses to the following statement: "I was able to handle difficult situations during this shift".

2.3.2. Covariates

In addition to the primary outcome measure, we included two covariates:

- Participants were asked if they sought assistance from the floor manager during their shift. They could indicate if they requested no assistance, some assistance, or much assistance during their shift.
- Participants were asked to indicate whether they had a morning, day, or evening shift. Night shifts were not included as the helpline protocol is different from the other shifts.

2.3.3. Secondary outcome measure: AI-assisted tool usage

Participants could indicate that they did not use, sometimes used, or frequently used the AI-assisted tool during their shift. The counselors' usage of the tool was examined by analyzing the frequency and duration of their interactions, using the date and time of the messages in the corresponding conversations. Moreover, we labeled the interaction for each instance when a counselor accessed the AI-assisted tool. This labeling was separately carried out by the researchers SS and NvE and encompassed two primary aspects. First, we determined whether the AI-assisted tool provided applicable information, and second, whether the counselor incorporated information from it. If the researchers disagreed with the label, the situation was examined and discussed by both authors until a consensus was achieved.

Additionally, we observed instances where counselors accessed the AI-assisted tool at potentially inappropriate times, seemingly for testing purposes. We identified four such cases: when the tool was queried after the counselor had already responded, when the help seeker was in the midst of composing multiple messages and had not yet finished, and when the counselor queried at the very start or the very end of a conversation. Table 1 shows the labels and their definitions.

2.4. Statistical analysis

A mixed-effects analysis was performed to predict the primary outcome of the statement "I was able to handle difficult situations during this shift", based on the group to which the counselor belonged (experimental condition or control condition). In this context, the outcome of this question served as the dependent variable, and the group represented the independent variable. The type of shift (morning, afternoon, and evening) and whether they received assistance from a floor manager were included as covariates.

2.5. Support tool

The supplementary file provides an overview of the AI-assisted tool pipeline, including the architecture of the network, the training method and technical details of the interface and dataset for training.

2.5.1. Interface

The suicide prevention helpline utilized a browser-based chat program as a means of communication with help seekers. The AI-assisted tool was implemented as a browser extension that functioned by analyzing the conversation when counselors requested support. The chat information was transmitted to a server, where embedding and retrieval processes took place. The resulting information was then sent back to the counselor and displayed within the tool.

Fig. 2 showcases the user interface of the tool. The tool presents the counselor with five alternatives, corresponding to the top five most similar embeddings determined by Cosine Similarity scores. The three preceding messages leading to the suggestion were also displayed to allow for comparison with the counselor's conversation. The suggestion itself was clearly labeled at the bottom. The counselor could cycle through the five suggestions using the previous and next buttons. If the conversation progressed and the counselor desired new suggestions, they could request them by clicking a dedicated button. It is worth noting that the tool intentionally disabled the copy-and-paste functionality to encourage counselors to rephrase the suggestion to align with their individual conversation style.

2.5.2. Support-tool database

The dataset utilized for the database of the AI-assisted tool consisted of chat interactions from previous chat conversations from the 113 Suicide Prevention, the national Dutch suicide prevention helpline. These chat interactions included both pre-chat and post-chat information filled in by the help seekers. Notably, only chats that received a positive rating from the help seekers were included in the dataset, ensuring a focus on successful counseling sessions.

Chat conversations were anonymized and help seeker and counselor names were given generic tokens. This was done by replacing usernames in the dataset. Furthermore, the deduce library for anonymization of clinical texts was used to further anonymize other components, such as locations and names of third parties.

The final dataset comprised a total of 187,000 messages exchanged during 3,816 chat sessions. From these messages, 91,252 unique embeddings were generated, representing potential suggestions that can be provided by the AI-assisted tool.

2.5.3. Ethics approval

The study protocol is performed in accordance with the relevant guidelines. This study was reviewed and approved by the Medical Research Ethics Committee of Amsterdam Universitair Medisch Centrum (registration number: 2022.0855).

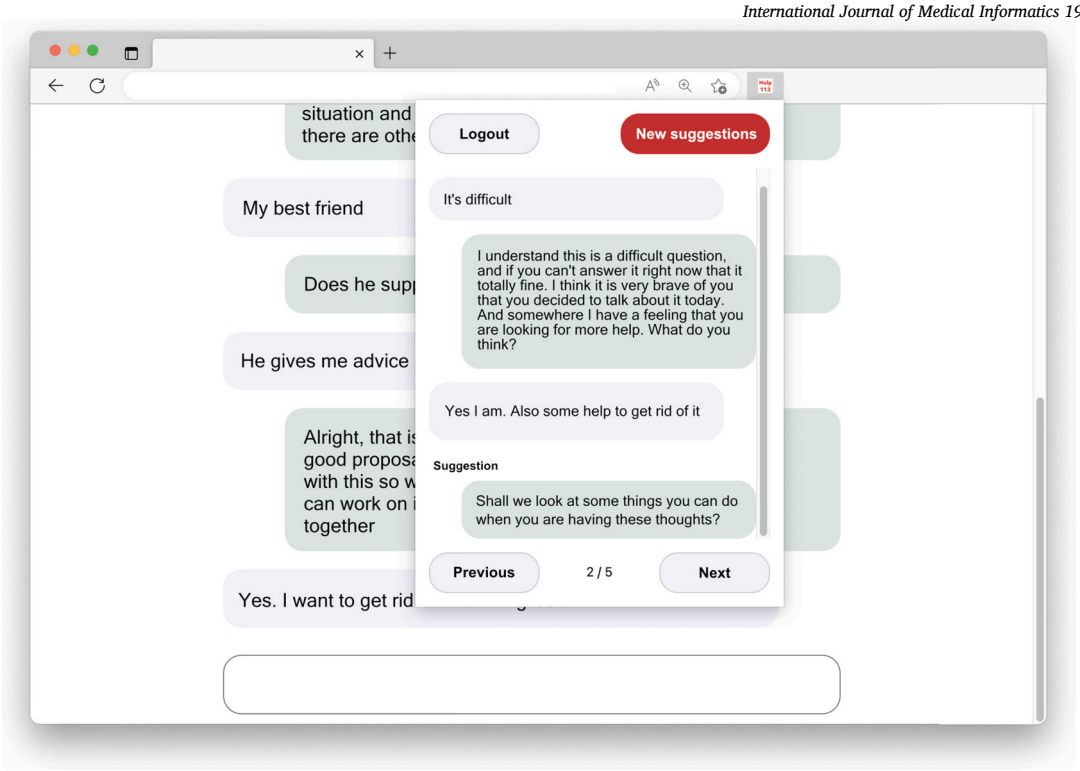

Fig. 2. Interface of the AI-assisted tool.

3. Results

3.1. Study sample

For the initial recruitment period, 40 counselors signed up to participate. After the start of the trial, only 15 counselors completed the questionnaires. The second recruitment period included an additional 33 participants who completed the questionnaires. In total, 48 participating counselors participated in the experiment: 27 counselors in the experimental condition and 21 counselors in the control condition. The flow of the participants through the trial is shown in Fig. 3. 167 questionnaires were completed: 93 in the control condition (on average 4,4 per counselor) and 74 in the experimental condition (on average 2,7 per counselor).

3.2. Primary outcome: counselor self-efficacy

We did not observe a significant difference in the self-reported score for the counselor's ability to handle difficult situations ($p = 0.36$). The AI-assisted tool condition scored an average of 7.54 on self-efficacy ($SD = 2.2$), while the control tool condition scored an average of 7.9($SD = 1.9$).

3.3. Secondary outcomes

3.3.1. Response time and conversation duration

The response time of counselors using the support system was 43.8($SD = 11.9$) seconds, which is slightly lower than 47.3($SD = 27.3$) for regular conversations but not significantly different ($p = 0.32$). The AI-assisted tool is used in longer conversations ($p < 0.001$), lasting on average 66.2($SD = 19.1$) minutes compared to regular conversations, which last on average 52.2($SD = 26.4$) minutes.

3.3.2. Support tool performance

Table 2 illustrates the coding of instances in which the AI-assisted tool was accessed. The results showed that the support-tool was utilized in 188 situations, in which eight situations involved corrupted data points, leaving 180 total labeled instances. Excluding irrelevant situations involving tool queries at the beginning (greeting) or end (goodbye), likely representing moments where the counselor was testing the tool, 152 queries remained. Among these, 103 (67%) queries received useful responses from the AI-assisted tool.

Table 2
The number of (not) useful suggestions during conversations, as well as the suggestions that were copied, elements taken from or where the counselor used something different.

	All situations	Relevant situations	Relevant situations & correct usage
Useful	113	103	53
Not Useful	67	49	11
Copied	28	25	15
Elements	36	34	21
Different	110	93	28
Total	180	152	64

However, this includes situations where the counselor queried the tool after providing their own response or while the help seeker was still typing. When these situations were also filtered, it resulted in 64 remaining queries, of which 53 (83%) were deemed useful. There was a noticeable gap in chat situations, where the tool was queried at the appropriate time. In many cases, the AI-assisted tool was queried after the counselor had already responded, suggesting a potential lack of initial trust in the tool. Of the 53 instances where the tool was considered useful, 15 (28%) instances involved counselors copying the suggestion, 21 (40%) instances in which elements from the suggestions were incorporated and 17 (32%) instances in which the counselor used a different response.

3.3.3. Frequently used situations

After further inspection, the cases in which the AI-assisted tool may find the best recommendations can be described as messages from the helpseeker that are relatively concise, such as questions or remarks. Fur-

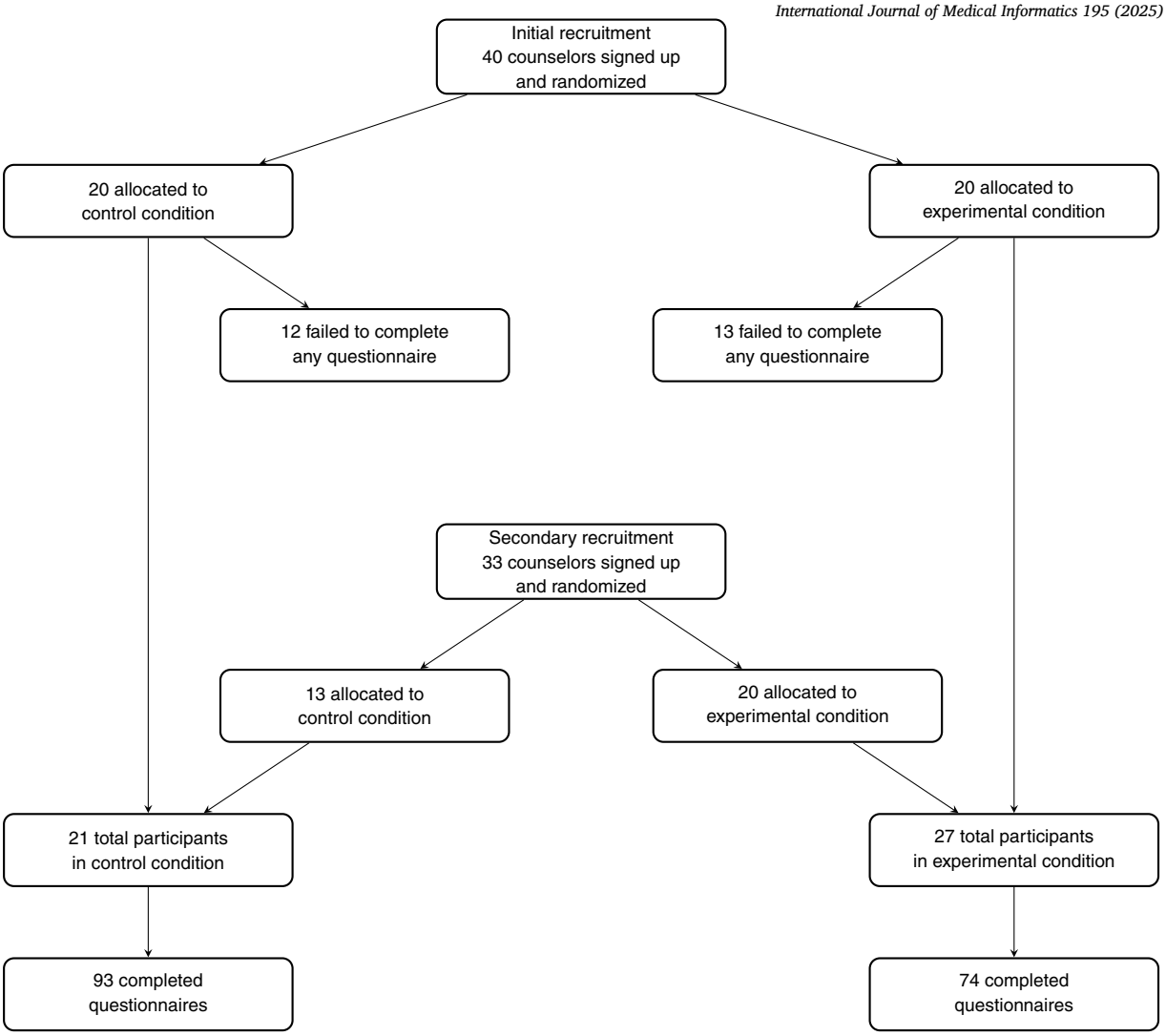

Fig. 3. Flow of participants through the trial.

thermore, when a scenario frequently occured in the corpus, it would be easier to find better recommendations. Similarly, when the messages are longer, or describe specific and personal situations, then it would be more difficult to find good recommendations. The tool was frequently employed in situations where the conversation was passed from triage to counselor. This transfer could have occurred because the counselor was testing the tool. However, the first step in any conversation is for the counselor to read the triage conversation, which therefore could indicate the need for a summarization feature. In cases where the counselors adopted the recommendation given in their response, the types of responses covered a broad range of situations. One common situation that was frequently queried was a scenario in which a help seeker was reluctant to talk about their suicidality to people in their environment. Furthermore, we observed that some counselors would adopt recommendations from the tool more frequently than others, indicating experience or personal style might be a component.

4. Discussion

4.1. Principal findings

In this study, we developed and evaluated a retrieval-based AI-assisted tool designed for use during counseling chat conversations. Because similar tools are lacking, this is a good step toward integrating real-time artificial intelligence (AI) in helplines. Our analysis examined self-efficacy, response time, conversation duration, and AI-assisted tool performance. The findings provide valuable insights into the tool's impact on counselor performance and user engagement.

Whereas many attempts were made to use AI as a counselor [12] [13], through the use of chat bots, they had difficulty performing at the standards of mental health professionals [14], which created ethical concerns [15]. Our study shows a possible application of assisting humans with AI.

The AI-assisted tool did not indicate an overall increase in counselors' confidence in handling difficult situations during their shifts. We did, however, observe that, in the intended use case, the tool produced a high percentage of relevant content. Furthermore, the longer duration of discussions may indicate that the tool was used in deeper or more difficult conversations. We observed no significant impact on the response times of counselors, indicating that the AI-assisted tool did not cause a delay in the counselor responding to the help seeker. The observed gap in tool usage at the appropriate time needs to be addressed. This issue could be mitigated by building trust and improving the suggestion retrieval capabilities, combined with training to familiarize counselors with the tool. Potentially the tool could prompt the counselor automatically after a certain duration of time that the counselor is not acting. Encouragingly, when correctly used, the tool demonstrated a high percentage of usability, with counselors adapting two-thirds of these usable suggestions. The remaining third of instances that were not adopted could be explained by counselor style or the poor fit to the current

conversation stage. However, these features are difficult to capture. We found concise questions to provide the most consistently good responses. This feature of the support system would be less suited for in-depth therapy sessions but could be very useful for assisting new counselors in quickly becoming accustomed to these situations.

Our study aligns with the current advancements in data analytics, NLP, and deep learning to enhance online mental health helplines. Our findings lay the groundwork for AI to assist helpline professionals. Ethical concerns [16] about harmful instructions are addressed by using only human-generated content, within its context, and by always having a human counselor make the final decision on what to write. This work underscores the potential of AI-based systems to assist counselors in navigating challenging helpline interactions, contributing to the broader goal of reducing suicides and suicide attempts.

4.2. Limitations

It is essential to acknowledge the study's limitations, such as the relatively small sample and lack of appropriate power. Future research could explore interventions to address the observed lack of initial trust in the tool, potentially through targeted training of new employees. Further enhancements to the tool, including a summarization feature, could be considered based on identified patterns of usage. As observed in the results, when long descriptive scenarios are given by the help seeker, it is difficult to find relatable content at a glance. We found that long text input finds messages of equal length, which requires more time for the counselor to read, so it is not immediately apparent if the suggestion is relevant.

4.3. Implications and future work

The observed characteristics of good performance in frequently occurring situations and short to medium-length responses lend itself as a useful means to assist new counselors. The tool could be introduced in the training, in order to increase the trust in the system. An interesting avenue for future work would be to compare this application of a recommender AI-assisted tool to a generative AI-assisted tool. Using the recently popularized large language models (LLMs), a model could be trained on counseling data to generate recommendations instead of retrieving them from a database. While counselors did indicate in previous research that they would have trouble trusting AI tools that generate information, it would be interesting to see if this sentiment remains with how much the capabilities of LLMs have improved. This approach would also address one of the limitations of finding relevant content through the long descriptive scenarios that help seekers give. However, this approach must be taken with care, as the reliability of LLMs in the mental health field is still a topic of discussion [17] In the short term, the AI-assisted tool can already provide feedback during a decent percentage of the requests of difficult situations. With the findings of this study, helpline counselors can be better instructed in the optimal times to use the AI-assisted tool. Furthermore, the barrier to access can be lowered, by removing some of the necessary components for the study, such as the login codes.

5. Conclusion

While the study did not significantly affect counselors' self-efficacy and the usage was relatively low, the tool was highly relevant in most situations where support was needed. This finding that the tool was used in longer conversations led us to believe that the tool was possibly utilized as a support mechanism to alleviate mental fatigue acting as a resource to assist counselors coping with the extended cognitive demands of lengthy conversations. Despite the limitations, the study lays the groundwork for advancing real-time AI in helplines. Future research should explore interventions to address initial trust issues and consider enhancements such as a summarization feature.

6. Summary table

6.1. What was already known on the topic

- **High cognitive load in counseling:** Online counseling for suicide prevention requires counselors to manage high cognitive loads during conversations, which can be challenging and contribute to high turnover rates.
- **Existing AI Tools:** Prior studies have explored various tools to assist counselors, such as live topic modeling (Dinakar et al.) and retrieval-based chatbots (Demasi et al.), which aim to provide real-time support by suggesting relevant conversation topics or responses.

6.2. What this study added to our knowledge

- **Real-Time application of AI:** This study demonstrated the practical application of an AI-assisted tool using deep learning-based sentence embeddings in real-time suicide prevention helpline conversations, highlighting both its potential and limitations.
- **Usability and profiency:** The study revealed that while the AI tool provided relevant suggestions in a majority of appropriate instances, counselors often used the tool in suboptimal moments due to potential trust issues or lack of proficiency.
- **Groundwork for future research:** By identifying the benefits and pitfalls of the AI tool, this study sets the stage for future research to address issues and optimize the timing of tool usage, possibly incorporating advanced features like conversation summarization or exploring the use of generative AI models.

CRediT authorship contribution statement

Salim Salmi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Saskia Mérelle:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Nikki van Eijk:** Writing – review & editing, Validation, Project administration, Methodology, Data curation. **Renske Gilissen:** Writing – review & editing, Supervision, Conceptualization. **Rob van der Mei:** Writing – review & editing, Supervision, Conceptualization. **Sandjai Bhulai:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

Generative AI was to improve readability and language only. The initial and final drafts of the paper were written exclusively by the authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijmedinf.2024.105760.

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