PARTNER: A Persuasive Mental Health and Legal Counselling Dialogue System for Women and Children Crime Victims

Priyanshu Priya, **Kshitij Mishra**, **Palak Totala** and **Asif Ekbal**
Department of Computer Science and Engineering, Indian Institute of Technology Patna, Bihar, India
{priyanshu_2021cs26, kshitij_1921cs23, totala_2001cs84, asif}@iitp.ac.in

Abstract

The World Health Organization has underlined the significance of expediting the preventive measures for crime against women and children to attain the United Nations Sustainable Development Goals 2030 (promoting well-being, gender equality, and equal access to justice). The crime victims typically need mental health and legal counselling support for their ultimate well-being and sometimes they need to be persuaded to seek desired support. Further, counselling interactions should adopt correct politeness and empathy strategies so that a warm, amicable, and respectful environment can be built to better understand the victims' situations. To this end, we propose **PARTNER**, a **P**oliteness and emp**A**thy strategies-adaptive pe**R**suasive dialogue sys**T**em for me**N**tal health and **LE**gal counselling of c**R**ime victims. For this, first, we create a novel mental **HE**alth and leg**A**l counse**L**ling conversational dataset **HEAL**, annotated with three distinct aspects, *viz.* counselling act, politeness strategy, and empathy strategy. Then, by formulating a novel reward function, we train a counselling dialogue system in a reinforcement learning setting to ensure correct counselling act, politeness strategy, and empathy strategy in the generated responses. Extensive empirical analysis and experimental results show that the proposed reward function ensures persuasive counselling responses with correct polite and empathetic tone in the generated responses. Further, **PARTNER** proves its efficacy to engage the victim by generating diverse and natural responses.

1 Introduction

According to the World Health Organization (WHO), the increase in the number of crimes against women[1] and children[2] (CAW&C) has become a major public concern with repercussions on various societal levels. WHO highlights the social and economic costs of violence and its negative impact on women's and children's health and well-being. Thus, there is a growing need to combat crime against women and children for accomplishing the United Nations Sustainable Development Goals (SDGs) 2030. The prevention/reduction of CAW&C is central to ensuring healthy lives and promoting well-being, achieving gender equality and women empowerment, fostering child development, ensuring equal access to justice and promoting peaceful and inclusive societies for all.

Women and children who have been victimized or are at risk of any violence need to have access to quality services, including medical care or mental health support and legal assistance. However, there is a global scarcity of mental health professionals[3].Also, the victims often fear stigmatization and societal condemnation and thus, hesitate to seek psychological support and/or are reluctant to report crimes. The issue is compounded by the fact that access to legal aid is constrained[4]. An artificial intelligence (AI)-assisted mental health and legal counselling dialogue system that can effectively interact with the victims and understand them could bridge the gap by serving as the first point of contact for them. Such an automated system can facilitate counselling sessions or assist the counsellors, thereby enhancing the accessibility to required counselling services for the victims.

It is imperative for the counselling bot to understand the victims' intended requirements and perform the action (counselling act) accordingly in order to provide adequate and pertinent assistance during counselling. One of the important actions required during counselling is persuasion. A persuasive attitude is necessary to facilitate therapeutic change [Abroms, 1968]. Persuasion is shown to be beneficial in improving the users' health-related self-management competencies [Orji, 2014]. Through persuasion, a counselling conversational bot can convince the users to follow specific advice, change their attitudes and beliefs in their own best interest and assist them in developing a sense of readiness to seek expert assistance. Besides, the counselling bot should behave politely and empathetically with the victims to elicit posi-

[1]https://www.who.int/news-room/fact-sheets/detail/violence-against-women
[2]https://www.who.int/news-room/fact-sheets/detail/violence-against-children
[3]https://www.who.int/publications/i/item/9789240036703
[4]https://www.unodc.org/documents/justice-and-prison-reform/LegalAid/Global-Study-on-Legal-Aid_Report01.pdf

Speaker	***Utterance***	***Response Type***
Victim	I am getting anxiety attacks after that incident. I often panic and feel restless. Help me.	
Bot	~~Don't worry and tell us which incident you are talking about?~~	Generic Response
	~~Don't worry, we will surely help. Could you please tell us which incident you are talking about?~~	Politeness strategy-adaptive Response
	~~We understand that anxiety attacks are scary and painful. Don't worry, we will surely help. Can you please let us know which incident you are talking about?~~	Politeness and Empathy-strategies-adaptive Response
	We understand that anxiety attacks are scary and painful. Don't worry, we will surely help. A small step can relieve you from all pains, trust us and please let us know which incident you are talking about?	Politeness and Empathy strategies-adaptive Persuasive Response

Table 1: Example showcasing the use of politeness (negative politeness) and empathy (emotional support) strategies with the appropriate counselling act (persuasion) in counselling.

tive outcomes in supportive conversations [Lucas *et al.*, 2014; Norcross, 2002; Robert *et al.*, 2011]. While counselling the victims, the bot must assess their mental and emotional state and tailor the conversation accordingly. Further, the bot needs to establish trust and rapport with the victims to provide effective counselling support. The use of polite and empathetic language displays a credible and cordial impression of the bot. Therefore, the bot should employ different politeness and empathy strategies as per conversation context to ensure a warm, amicable and respectful atmosphere for the victims and to build an emotional connection with them. The example given in Table 1 depicts how the incorporation of politeness and empathy strategies together with persuasive behaviour eventually contributes to a better personalized experience and motivates user engagement.

Considering the importance of mental health and legal support for the victims and the relevance of politeness, empathy and persuasion in counselling conversations, we propose **PARTNER**, a **P**oliteness and emp**A**thetic strategies-adaptive pe**R**suasive dialogue sys**T**em for me**N**tal health and l**E**gal counselling of c**R**ime victims. However, developing such a dialogue system is challenging due to the subjective nature of politeness, sophisticated and nuanced ways of expressing empathy, and the intricate techniques of counselling. Further, scarcity of a counselling dialogue data poses a restriction in the development of such systems that can generalize to diverse users in different scenarios.

Therefore, first, we create **HEAL**, a novel mental **HE**alth and leg**A**l counse**L**ling dataset consisting of counselling conversations between the bot and a crime victim. Second, inspired by the recent success of reinforcement learning (RL) [Casanueva *et al.*, 2018; Mesgar *et al.*, 2020; Mishra *et al.*, 2022a] in fine-tuning a Cross-Entropy loss based model, when trying to ensure some defined aspects in generation, we develop our proposed dialogue system in an RL framework. Our proposed system **PARTNER** learns from user interactions and improves depending on the users' feedback in the form of rewards. Specifically, a novel reward function is designed consisting of five rewards to ensure counselling act consistency, correct use of different politeness and empathy strategies, fluency and diversity in generated responses.

The *key* contributions of our current work can be summarized as follows: **(i)** Created a novel large-scale dataset, **HEAL** annotated with counselling act, politeness, and empathy strategies for mental health and legal counselling of crime victims; **(ii)** Designed robust transformer-based counselling act, politeness strategy, and empathy strategy classifiers; **(iii)** Designed a novel reward function to assess generated responses in terms of naturalness, user retainment, and correctness of counselling act, politeness and empathy strategies; **(iv)** Proposed **PARTNER**, RL-based politeness and empathy strategies-adaptive persuasive dialogue system for mental health and legal counselling of crime victims; **(v)** Performed extensive automatic and human evaluation to demonstrate the effectiveness of our proposed system[5].

Societal Impact. Psychological and/or legal counselling are the key elements for strengthening the social, emotional and mental well-being of the victims and for securing their access to justice. These are also fundamental for reducing the inequalities and vulnerabilities that leave people behind and undermine the potential of individuals and of humanity as a whole. Our research which aims at the dialogue generation module in mental health and legal conversational system can be viewed as a step towards achieving the overarching objective of the SDGs 2030 agenda to "*leave no one behind*". We believe that our current work would be beneficial to the victims as well as the counsellors, law enforcement agencies, NGOs, and other support groups by ensuring 24x7 assistance for the victims.

2 Related Work

The crime victims often suffer from short-term and/or long-term physical and/or mental issues, hence they require both mental health as well as legal assistance for their overall physical, mental, and emotional recovery after victimization [Roberts, 2002; Williamson *et al.*, 2010]. Though there have been attempts to build chatbots for mental health support [Fitzpatrick *et al.*, 2017; Fulmer *et al.*, 2018] or legal assistance [John *et al.*, 2017], research on dialogue systems in the mental health and legal domain for victims is still in the nascent stage. A few rule-based chatbots have been reported in the literature that aims to help the victims of a particular type of crime like *You are not alone* (domestic violence), *Hello Cass* (sexual harassment), *Law*, etc. Due to dependency on rules, these systems are neither scalable nor generalizable. Further, some of these systems emphasize solely on solving

[5]Codes and data can be accessed at PARTNER or https://www.iitp.ac.in/∼ai-nlp-ml/resources.html#PARTNER

mental health issues while others are designated to help victims in legal cases.

Studies have reported that dialogue systems to support victims should be 'high performing' (effective with information), 'smart' (accurate and correct) and 'personable' (personalizing information)[6]. Thus, depending upon the victim's need, the bot should carry out relevant actions, like persuading the victims, offering counselling support/legal aid, or performing casual actions like information seeking/delivery. Persuasion has been regarded as a crucial aspect in the counselling process [Strong, 1968; Heppner and Claiborn, 1989]; counsellors adhering to persuasive techniques are perceived to play an active role during counselling [Dorn *et al.*, 1986]. Recently, there has been an increased interest in making the agent persuasive that can bring positive change and/or improve knowledge, awareness, or understanding to help people achieve better health [Fogg, 2002; Althoff *et al.*, 2016; Demasi *et al.*, 2019; Liang *et al.*, 2021]. Persuasive dialogue systems have been applied in the legal arena as well [Gordon, 1993].

While a few prior works attempted to build counselling dialogue systems for providing personalized support (asking personalized questions and delivering personalized information) to the victims [Kim *et al.*, 2022], incorporating more humanly quotient like politeness and empathy into these systems remains unexplored. Studies have proven that politeness and empathy are crucial for providing effective counselling support [Lucas *et al.*, 2014; Norcross, 2002; Robert *et al.*, 2011]. Politeness contributes to a sense of compassion and aids the disclosure of sensitive information [Lucas *et al.*, 2014; Kim *et al.*, 2018]. Empathetic interactions are crucial in establishing a therapeutic bond and rapport [Norcross, 2002; Robert *et al.*, 2011] and there is substantial evidence that demonstrates that empathy is helpful in reducing symptom severity in mental health support seekers [Elliott *et al.*, 2018]. The authors in [Saha *et al.*, 2022a; Saha *et al.*, 2022b] explored the ways to induce empathy in the mental health dialogue system to reflect an emotional attachment with the users.

The existing research on mental health or legal intervention systems for victims primarily focused on delivering generic support, which is perhaps more akin to a self-help book and thus, often fails to cater to the urgent needs of the victims. In comparison, our proposed system enquires about the incident, assesses the immediate psychological needs, and suggests local or national-level resource channels or coping methods for certain forms of victimization. In addition, instilling socially desirable behaviour like politeness, empathy and/or persuasiveness was totally unexplored in earlier works. Our work further differentiates in the sense that we focus on a new task of developing an end-to-end counselling dialogue system for crime victims where five novel rewards force a dialogue agent to adopt different counselling acts (including but not limited to persuasion), politeness and empathy strategies based on the conversational context. The study close to our work is [Mishra *et al.*, 2022b], which attempts to incorporate politeness strategy and emotion in the agent's responses to enhance its persuasiveness for social good. Following [Mishra *et al.*, 2022b], we train our system with standard Proximal Policy Optimization (PPO) [Schulman *et al.*, 2017] designing five different novel rewards pertaining to our task. To the best of our knowledge, this is the first attempt to build such a counselling dialogue system for crime victims.

[6]https://www.filesforprogress.org/memos/sexual-assault-victims-want-services-tailored-to-needs.pdf

3 Dataset

Our proposed dataset **HEAL** comprises conversations between a victim of crime and a conversational bot. The purpose of these interactions is to inspire and uplift the victims, ultimately assisting them in restoring their physical and emotional well-being by offering relevant mental health and/or legal support to them.

3.1 Data Preparation

The primary focus of **HEAL** is to address the mental health and legal needs of women and children who have experienced various crimes such as domestic violence, acid attacks, cyberstalking, online harassment, impersonation, etc. In order to offer genuine support and counselling services to the victims, various sources such as National Cybercrime Reporting Portal, National Commission for Women, Ministry of Women and Child Development, Criminal Law Amendment Act 2013 and Information Technology (Amendment) Act 2008 are referred during data preparation. Additionally, real-life stories of crimes against women and children are gathered from multiple websites. These stories, along with the information gathered from the various sources, are then given to four annotators who have post-graduate qualifications in English linguistics and substantial experience in related tasks. Based on this information, the annotators are instructed to create dialogues between a counselling bot and a victim using a well-known Wizard-of-Oz approach [Kelley, 1984], where one annotator assumes the role of the *counselling bot* and the other acts as the *victim*.

To eliminate any correlation between the counselling acts or politeness strategies or empathy strategies of the counselling bot and the targeted victim's characteristics, one of the two annotators is randomly assigned the role of either the *counselling bot* or the *victim*. In order to prepare the counselling dataset and annotate it with suitable counselling acts, politeness, and empathy strategies, the annotators are provided with specific guidelines to follow. These guidelines are mentioned below:

Data Preparation Guidelines. To develop the guidelines, we collaborated with mental health and legal experts from government institutions. The guidelines are outlined as follows:

1. **Build relationship:** The counselling bot should strive to establish a harmonious relationship with the victims by demonstrating a caring and amicable attitude towards them;
2. **Identify the problem:** The counselling bot should aim to recognize the difficulties faced by the victim and understand the root causes of these difficulties;
3. **Facilitate change:** The counselling bot should utilize suitable tactics and interventions to foster a constructive

shift in the victim's circumstances and emotional state: (i) Imbibe politeness in the bot's responses to uncover the victim's innate qualities and maintain a seamless flow of conversation during counselling; (ii) Demonstrate care, warmth, and compassion to nurture a supportive environment and cultivate an empathetic bond with the victim.; (iii) Demonstrate comprehension of the victim's experiences and emotional state inferred from their responses, in order to foster a connection between the bot and the victim, and eventually facilitate the disclosure of concealed emotions and experiences; (iv) Maintain a tone of affirmation and positivity in the bot's responses to uplift the victim's self-esteem.;

4. **Evaluation and Termination:** Additionally, the bot should offer essential mental health and legal information/services (such as contact details of experts, medical care facilities, legal guidance, information about support groups, assistance with filing complaints, etc.) to the victims, when necessary. Subsequently, the bot should provide a set of safety tips to help prevent similar problems in the future.

Counselling Act. Counselling conversations demand carefully devising counselling acts capable of catering to the needs of users. Thus, we design a set of eight counselling acts to meet the adequate requirement of the victims and also be readily understandable in order to aid in the development of a counselling conversational system for the victims. These counselling acts are formulated under the supervision of domain experts. They are described below:

1. **Counselling support:** Provide various support services like medical help, mental health-related aid, NGOs information etc. during counselling based on the victim's need.
2. **Legal assistance:** Ensures legal assistance to the victims.
3. **Persuasion:** Assists the victims in developing a readiness to seek professional assistance by compelling them to adhere to specific recommendations, modifying their attitudes and beliefs in their own best interests, and fostering a sense of readiness to do so.
4. **Seek information:** Request for a few basic information in order to comprehend the problem and provide relevant assistance.
5. **Deliver information:** Provide information pertaining to the problem being discussed.
6. **Re-check assistance:** Inquires for further help or clarification about the problem under discussion.
7. **Greet:** Typically, each conversation begins with a greeting from one speaker and an appropriate response from the other.
8. **Closing remark:** Marks the end of the conversation.

Politeness and Empathy Strategies. In order to establish a personal, friendly, and empathetic connection with the victim during counselling, a counselling bot can employ various politeness and empathy strategies. The use of appropriate politeness strategies and empathy strategies by the counsellor can help minimize threats to the victim's self-esteem and demonstrate emotional and cognitive understanding of the victim's situation, respectively. We consider three well-known politeness strategies, namely positive politeness, negative politeness, and bald on-record, as outlined in Brown and Levinson's work [Brown *et al.*, 1987]. However, since there is a lack of well-defined empathy strategies in mental health and legal counselling, based on the drafted guidelines, we formulated seven empathy strategies, considering the significance of empathy in counselling [Norcross, 2002].

To ensure consistency and make necessary adjustments, the four aforementioned annotators are paired with each other, resulting in six unique pairs, and they generate a total of 48 conversations. Discrepancies in the strategies are analyzed, and modifications are made under the guidance of domain experts. Once all seven empathy strategies are approved by the domain experts, they are applied to all conversations. The empathy strategies are as follows:

1. **Reflective listening:** Demonstrates a genuine curiosity to learn and delve deeper into the details shared by the victims, creating a sense that the bot is genuinely interested in listening to them.
2. **Confidential comforting:** Displays genuine interest and concern for the privacy of the victims, providing assurance that any information shared will be treated with the utmost confidentiality.
3. **Evoke motivation:** Encourages the victims to embrace a forward-looking perspective and participate in activities that promote feelings of positivity and optimism.
4. **Express emotional support:** Provides emotional solace or words of encouragement to entirely comprehend the problems faced by the victims and the intensity of their emotions.
5. **Offer counselling:** Provides essential mental health and legal counselling advice, along with contact information of experts, whom the victim can reach out to for further guidance and assistance.
6. **Escalate assurance:** Reassures the victims that they are never to blame for any form of assault and firmly conveys the message that they are not alone, emphasizing that they can always seek help and support.
7. **No strategy:** Assigned to the utterances which do not utilize any empathy strategy.

3.2 Data Annotation

For our work, the *counselling bot*'s utterances in each dialogue are annotated with one of the eight counselling acts, three politeness strategies, and seven empathy strategies. For annotating the bot's utterances, we instruct the same four annotators to label every utterance of the bot with the given set of counselling acts, politeness strategy and empathy strategy labels. To strengthen the annotations, annotators are clearly briefed about the annotation guidelines along with illustrative examples for each of the counselling acts, politeness and empathy strategies before beginning the annotation procedure.

A reliable multi-rater Kappa [McHugh, 2012] agreement ratio of 79.4%, 83.7%, and 80.1% is observed for the counselling act, politeness strategy and empathy strategy, respectively, among all the four annotators. The dataset statistics are shown in Table 2.

Metrics	Train	Dev	Test
No. of Dialogues	162	22	32
No. of Utterances	4,133	407	664
Avg. Utterances per Dialogue	25.51	18.50	20.75

Table 2: Dataset statistics.

4 Proposed System: PARTNER

Our proposed system comprises of two components *viz.* Cross-Entropy Loss based Dialogue Model (*CELDM*) - to foster natural language interaction between the *counselling bot* and the *crime victim*, and Proximal Policy Optimization (PPO) Loss based Dialogue Model (*PLDM*) - to generate politeness and empathy strategies-adaptive counselling responses. *PLDM* further can be divided into two sub-components *viz.* Reward - uses counselling dialogue act, politeness and empathy strategies classifiers to calculate the respective rewards, and Policy Optimization - updates policy parameters to attain optimal policy. Each preceding component or sub-component is used by the succeeding component or sub-component, i.e. first a dialogue model is trained using cross-entropy loss, then to obtain the final **PARTNER**, it is fine-tuned with PPO loss.

4.1 Cross-Entropy Loss-based Dialogue Model

We represent the exchanges between the counselling bot and the crime victim as a multi-turn counselling dialogue, denoted as $d = \{cb_0, cv_0, .., cb_i, cv_i, .., cb_{T-1}, cv_{T-1}\}$. Here, cb_i and cv_i represent the i^{th} response from the counselling bot and the crime victim, respectively. Inspired by the approach in [Wu *et al.*, 2021], we employ two GPT2-small [Radford *et al.*, 2019] models, namely ρ_{cb} and ρ_{cv}, which are trained alternatively to approximate the distribution of utterances from the counselling bot (*cb*) and the crime victim (*cv*). Given the preceding context, ρ_{cb} and ρ_{cv} predict the next token gr_j to generate a response $gr = \{gr_1, gr_2, .., gr_j, .., gr_m\}$ comprising of m tokens. We can express the joint probability of both the victim's and the counselling bot's utterances as follows:

$$\rho_{pa}(cv_i|cv_{<i}, cb_{<i}) = \prod_{j=1}^{t_{cv_i}} P(gr_j|gr_{<j}, cv_{<i}, cb_{<i}) \quad (1)$$

$$\rho_{cb}(cb_i|cv_{<=i}, cb_{<i}) = \prod_{j=1}^{t_{cb_i}} P(gr_j|gr_{<j}, cv_{<=i}, cb_{<i}) \quad (2)$$

Finally, the dialogue model $\rho_\theta(d)$ is trained by minimising the cross-entropy loss between the predicted and ground truth probability distribution of utterances. Mathematically, $\rho_\theta(d)$ can be expressed as follows:

$$\rho_\theta(d) = \prod_{T=0}^{T-1} \rho_{pa}(cv_i|cv_{<i}, cb_{<i})\rho_{cb}(cb_i|cv_{<=i}, cb_{<i}) \quad (3)$$

4.2 PPO Loss based Dialogue Model

In order to strengthen appropriate counselling dialogue acts, empathy, and politeness strategies with the generation of diverse yet natural responses, we begin by developing a novel reward function encompassing five distinct rewards tailored to specific aspects. Subsequently, the value of this reward function is utilized in the PPO loss to fine-tune the dialogue model $\rho_\theta(d)$ generating a set of n-candidate responses based on a given context. These set of responses are quality checked in terms of different aspects using five rewards.

Rewards

Our proposed reward function R incorporates two types of rewards. First, we have task-specific rewards, namely R_1 - ensuring appropriate counselling dialogue acts, R_2 - incorporating correct empathy strategies, and R_3 - enforcing politeness strategies in the generated responses. Secondly, we include generic rewards, specifically R_4 to measure user retainment and R_5 to assess the naturalness. The formulation of the reward function R is as follows:

$$R = \beta_1 R_1 + \beta_2 R_2 + \beta_3 R_3 + \beta_4 R_4 + \beta_4 R_5 \quad (4)$$

where, $\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 = 1$.

Counselling Dialogue Act Consistency Reward. To ensure consistency in the generated responses, we fine-tuned a RoBERTa-large [Liu *et al.*, 2019] based counselling dialogue act classifier. Each generated candidate is passed through this classifier to predict the counselling dialogue act and then it is compared against the gold response labels. Deviations from the expected act are penalized.

$$R_1 = \mathcal{P}_{cda}(cb_T) - \gamma \sum_{i \in C_{CDAL}} \mathcal{P}_{cda_i}(gr_T) \quad (5)$$

where, $C_{CDAL} = \{0, 1, 2, 3, 4, 5, 6, 7\}$ represents the set of counselling dialogue act labels, $\mathcal{P}_{cda}(cb_T)$, and $\mathcal{P}_{cda_i}(gr_T)$ gives the predicted counselling dialogue act probabilities for ground truth and generated utterance, respectively. To control the penalization, we introduce the factor γ, where higher values of γ result in more severe penalties [7].

Empathy and Politeness Strategy Rewards. To incorporate empathy and politeness strategy rewards, we utilize dedicated classifiers. For this purpose, we fine-tune a RoBERTa-large model [Liu *et al.*, 2019] using empathy strategy labels $C_{ESTL} = 0, 1, 2, 3, 4, 5, 6$ and politeness strategy labels $C_{PSTL} = 0, 1, 2$. In order to enforce correct empathy and politeness strategies, at each turn T, we compare the predicted labels for empathy and politeness strategies for the generated response gr_T with their respective ground truth response labels. Any responses that deviate from the ground truth labels are penalized accordingly. The rewards for empathy strategy (R_2) and politeness strategy (R_3) can be formulated as follows:

$$R_2 = \mathcal{P}_{est}(cb_T) - \gamma \sum_{i \in C_{ESTL}} \mathcal{P}_{est_i}(gr_T) \quad (6)$$

$$R_3 = \mathcal{P}_{pst}(cb_T) - \gamma \sum_{i \in C_{PSTL}} \mathcal{P}_{pst_i}(gr_T) \quad (7)$$

where, at a turn T, $\mathcal{P}_{est}(cb_T)$, $\mathcal{P}_{pst}(cb_T)$ corresponds to the ground truth empathy and politeness strategy predicted probabilities, and $\mathcal{P}_{est_i}(gr_T)$, $\mathcal{P}_{pst_i}(gr_T)$ gives the predicted probabilities for empathy and politeness strategies respectively.

[7] γ is set to be greater than or equal to 1

Retainment Reward. A counselling dialogue should be interactive and engaging, hence, should be able to retain the victim by generating diverse responses. Therefore, retainment reward R_4 is designed considering two dialogue quality factors *viz.* lexical level and sentence level similarities, calculated here as the Jaccard similarity [Jaccard, 1912] and cosine similarity between gr_T and gr_{T-1} at turns T and $T-1$, respectively.

$$R_4 = \frac{1}{2}\left(\cos(gr_T, gr_{T-1}) + \left(\frac{gr_{T-1} \cap gr_T}{gr_{T-1} \cup gr_T}\right)\right) \quad (8)$$

Naturalness Reward. To reinforce that a counselling dialogue system generates natural responses of high linguistic quality, we first compute the Negative Log-Likelihood (NLL) of the generated responses. Then, to scale down the values within the range of 0 and 1, we apply the $\tanh()$ function[8] to the NLL as formulated below:

$$R_5 = -\tanh(NLL) \quad (9)$$

Policy

The action selection of a conversational bot can be described by a policy, which is a probability mapping function denoted as $\mathcal{P}_\theta$. This function generates a feasible response gr comprising of m tokens, which can be considered as an action, given a particular context representing the current state.

$$\mathcal{P}_\theta(gr_{1:t}|x) = \prod_{k=0}^{m} \mathcal{P}_\theta(gr_k|y_{<k}, x) \quad (10)$$

Proximal Policy Optimization (PPO). Policy updates are performed at each step using PPO-loss, which effectively ensures low variance compared to the old policy. The optimization of the policy can be formulated in three steps. Initially, gradient ascent is applied to the loss function $J(\theta)$ in order to maximize the expected reward:

$$\nabla_\theta J(\theta) = E_{r\sim\mathcal{P}_\theta}[\nabla_\theta \log \mathcal{P}_\theta(r)\hat{A}_r] \quad (11)$$

Secondly, in order to restrict large deviations, the *log* term in the optimization process is replaced with an importance sampling term. Additionally, clipping is employed to prevent catastrophic forgetting, ensuring that the updates do not have excessively large magnitudes:

$$L^{\text{CLIP}}(\theta) = \hat{E}[\min(pr_r(\theta)\hat{A}_r, \text{clip}(pr_y(\theta), 1-\varepsilon, 1+\varepsilon)\hat{A}_r)] \quad (12)$$

Here, the probability ratio between the new and old policies is calculated as $pr_r(\theta) = \mathcal{P}_\theta^{new}/\mathcal{P}_\theta^{old}$. ε and $\hat{A}_y$ gives the clipping range and estimated advantage (normalized rewards) respectively. Finally, the parameters are updated according to the following equation:

$$\theta_{k+1} = \underset{\theta}{\text{argmax}} \underset{s,a\sim\mathcal{P}_{\theta_k}}{E}[L^{\text{CLIP}}] \quad (13)$$

[8]The $\tanh()$ function maps values between -1 and 1, but in this case, the loss cannot be negative, so the resulting values will always be between 0 and 1. Moreover, sigmoid is not chosen as it would map values between 0.5 and 1.

	BERT-large		RoBERTa-large	
Classifier	**W-ACC**	**Macro-F1**	**W-ACC**	**Macro-F1**
Counselling strategy	0.881	0.849	0.904	0.891
Empathy strategy	0.912	0.864	0.940	0.909
Politeness strategy	0.926	0.918	0.952	0.952

Table 3: Evaluation results of the Empathy and Politeness strategy classifiers.

5 Experiments

Implementation Details. The pre-trained GPT2-small [Radford *et al.*, 2019] is utilized to train *CELDM*. The fine-tuning of the trained *CELDM* is conducted in an RL environment, with experiments carried out using different numbers of candidate responses ($n = 2, 3, 4, 5, 10$). Based on the obtained loss, the value of $n = 3$ is selected as the final choice. For decoding the generated candidates, nucleus sampling, following [Holtzman *et al.*, 2019], is employed with a temperature of $T = 0.8$ and a probability threshold of $p = 0.9$. During training, several parameters are considered: the seed value is set to 10, the human reward is set to 10, the maximum candidate length is limited to 50, and the AdamW optimizer [Loshchilov and Hutter, 2018] is employed with a learning rate of $\alpha = 2e^{-05}$, an epsilon value of $\varepsilon = 0.2$ and epochs = 20. The final weights chosen for the reward combinations are $0.3, 0.25, 0.2, 0.15, 0.1$ for β_1, β_2, β_3, β_4 and β_5 respectively. Lastly, a penalization factor of $\gamma = 2$ is set for rewards R_1, R_2 and R_3.

Evaluation Metrics. The performance of the proposed system, **PARTNER**, is evaluated through both automatic and human evaluations. The metrics employed to assess the performance of counselling dialogue act, empathy strategy, and politeness strategy classifiers are Weighted Accuracy (W-ACC) and Macro-F1. The efficacy of **PARTNER** is evaluated in terms of two aspects *viz.* task success (counselling, empathy, and politeness) and response quality (fluency, consistency, and response length).

For automatic evaluation, task success is measured using metrics such as **CoAct** (consistency of predicted counselling acts with ground truth), **EmpStr** (consistency of predicted empathy strategies with ground truth label), and **PolStr** (consistency of predicted politeness strategies with ground truth)[9]. Response quality is evaluated using metrics such as Perplexity (**PPL**) and response length (**R-LEN**).

Model	CoAct	EmpStr	PolStr	PPL	R-LEN
ARDM [Wu *et al.*, 2021]	52.8%	57.2%	66.1%	3.74	14.8
PARTNER-R	51.9%	57.3%	66.3%	3.68	14.4
PARTNER-GR	55.3%	59.1%	69.3%	3.17	15.7
PARTNER-TR	53.8%	58.2%	67.8%	3.31	15.4
PARTNER	**56.5%**	**61.8%**	**69.9%**	**2.55**	**16.06**

Table 4: Results of automatic evaluation. **PARTNER** refers to our proposed system considering all rewards. PARTNER-R, PARTNER-GR and PARTNER-TR refers to **PARTNER** with no rewards, without generic reward and without task-specific reward respectively.

To conduct the human evaluation, we recruited three eval-

[9]CoAct, EmpStr and PolStr is evaluated using counselling act, empathy and politeness strategy classifiers

Model	CounC	EmpC	PolC	Nats	Corr	NRep
ARDM	2.44	2.60	2.97	4.10	3.84	3.71
PARTNER-R	2.36	2.66	3.01	4.21	3.91	3.82
PARTNER	**3.06**	**3.11**	**3.42**	**4.52**	**4.14**	**4.07**

Table 5: Results of human evaluation.

uators holding postgraduate qualifications and having experience in the related works[10]. Initially, each evaluator engaged with the system ten times, with a fresh set of responses provided for each interaction. Subsequently, domain experts from government-run institutions are asked to cross-verify these 30 human-evaluated interactions to ensure the quality of the evaluation process. Upon passing the quality check, additional 45 interactions are evaluated, with each evaluator interacting and assessing 15 dialogues. As a result, we obtained a total of 75 human-evaluated dialogues. The human evaluation metrics encompass several aspects. For task success, we considered the correctness of the counselling act (**CounC**), empathy strategy (**EmpC**), and politeness strategy (**PolC**). To evaluate response quality, we focused on naturalness (**Nats**), correctness (**Corr**), and non-repetitiveness (**NRep**). All dialogue interactions were assessed on an integer Likert scale ranging from 1 to 5 [11]. The evaluation process exhibited an inter-evaluator agreement ratio of 75.1%.

6 Results and Analysis

To begin, the first step involves analyzing the sub-components, namely the counselling act, empathy, and politeness classifiers. Following that, the results of the proposed **PARTNER** system are presented and compared against four baselines: ARDM (*CELDM*) [Wu *et al.*, 2021], PARTNER-R (**PARTNER** with zero reward), PARTNER-GR (**PARTNER** without generic rewards), and PARTNER-TR (**PARTNER** without task-specific rewards). Table 3 provides an overview of the evaluation results for the classifiers. The results indicate that the classifiers perform well in terms of Weighted Accuracy (**W-ACC**) and Macro-F1. Moreover, it is observed that RoBERTa-large [Liu *et al.*, 2019] outperforms BERT-large [Devlin *et al.*, 2018]. The good scores obtained from the classifiers demonstrate their effectiveness in designing R_1, R_2, and R_3 rewards.

Automatic evaluation. Table 4 illustrates that **PARTNER** outperforms the baselines: ARDM, PARTNER-R, PARTNER-GR, and PARTNER-TR across all metrics. The metrics **CoAct**, **EmpStr**, and **PolStr** obtain good scores of 56.5%, 61.8%, 69.9% with a significant difference of $< 3.7, 4.6, 3.8 >, < 4.6, 4.5, 3.6 >, < 0.3, 2.7, 0.6 >$ and $< 1.8, 3.6, 2.1 >$, respectively in comparison to the baselines ARDM, PARTNER-R, PARTNER-GR, and PARTNER-TR[12]. These results provide justification for the design of our reward function in **PARTNER**. By incorporating task-specific rewards, the counselling bot is incentivized to generate appropriate counselling act, empathy, and politeness strategy-adaptive responses. These findings strengthen our hypothesis that rewards for counselling dialogue act consistency, empathy, and politeness strategies contribute to the development of a more engaging, persuasive, empathetic, and polite counselling dialogue system. Table 4 demonstrates that **PARTNER** achieves significantly high scores, with **PPL** and **R-LEN** = 2.55 and 16.06, respectively when compared to the baselines: ARDM, PARTNER-R, PARTNER-GR, and PARTNER-TR with a difference of $< 1.19, 1.26 >, < 1.13, 1.66 >, < 0.62, 0.36 >$ and $< 0.76, 0.66 >$, respectively. This can be attributed to the utilization of generic rewards, which encourage the model to establish a natural and smooth connection with the victim, resulting in interactive and engaging conversations. Additionally, it is worth noting that PARTNER-GR achieves lower **PPL**, while PARTNER-TR attains lower scores in **CoAct**, **EmpStr**, and **PolStr**, which highlights the importance of both generic rewards and task-specific rewards in the system, respectively.

Human evaluation. The evaluation results from the human assessment are presented in Table 5. A comparison between the proposed system, **PARTNER** and the baselines, ARDM and PARTNER-R, reveals that **PARTNER** achieves higher scores in **CounC**, **EmpC**, **PolC**, **Nats**, **Corr**, and **NRep** with a with a difference of $< 0.62, 0.70 >, < 0.51, 0.45 >, < 0.45, 0.41 >, < 0.42, 0.31 >, < 0.3, 0.23 >$, and $< 0.36, 0.25 >$, respectively. These results indicate that all four rewards have played a vital role in generating accurate, natural, and non-repetitive counselling utterances with politeness and empathy imbibed in them. Therefore, it can be concluded that incorporating rewards for empathy and politeness strategies enhances the ability of **PARTNER** to establish a connection with the victim by generating engaging and interactive responses.

7 Conclusion and Future Work

The prevention/reduction in CAW&C will foster a nurturing, equitable and secure environment for all, which consequently will improve mental health, ensure a safer and fairer world for all and thereby promote sustainable development. Taking into account the importance of preventing/reducing CAW&C in achieving the SDGs, in this paper, we proposed a politeness and empathy strategies-adaptive persuasive mental health and legal counselling dialogue system, **PARTNER** to help the crime victims by offering (or sometimes persuading them for seeking) pertinent counselling support in a cordial and compassionate setting. For this, we prepared a novel counselling conversational dataset, **HEAL** and utilized it to train **PARTNER** in an RL framework by designing novel rewards for facilitating correct counselling act, politeness and empathy strategies in the counselling bot's response. Detailed automatic and human evaluation results conclude that **PARTNER** is capable of performing adequate counselling act and adopt desired politeness and empathy strategies whilst ensuring engagingness and naturalness during the counselling session. A counselling system can cover different aspects of victim's personal traits to counsel each victim in a different way. This drives us towards future directions for our current research work.

[10] Evaluators are paid in accordance with the university norms.

[11] Rating of 1 denoted low and 5 represented high performance in the respective metric

[12] We performed a statistical significance test, Welch's t-test [Welch, 1947], and it is conducted at 5% (0.05) significance level.

Contribution Statement

Priyanshu Priya and Kshitij Mishra are jointly the first authors in this work. Subsequently, Palak Totala and Asif Ekbal are second and third authors respectively.

Ethical Statement

To avoid any possible harm or potential for harm, it is crucial for a counsellor (here, counselling dialogue system) to follow some ethics principles [Association and others, 2016]. All responses should be formed with upholding the victim's rights, maintaining appropriate professional competence, safeguarding the welfare of the victim, obtaining informed consent and delivering authentic information. Therefore, to create the dialogues in the dataset, first authentic websites and documents are referred to; then, the dataset is duly verified by experts from government-run institutions. A counselling dialogue system on the one hand can counsel and provide support, whereas, on the other hand, it can also be used to mould a person's beliefs, which poses a big challenge in the development of these systems. Due to the sensitivity of the data content and system, the codes and data would only be provided for research purposes through appropriate data agreement procedures.

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