USING PSYCHOLOGICAL CHARACTERISTICS OF SITUATIONS FOR SOCIAL SITUATION COMPREHENSION IN SUPPORT AGENTS

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ABSTRACT

Support agents that help users in their daily lives need to take into account not only the user's characteristics, but also the social situation of the user. Existing work on including social context uses some type of situation cue as an input to information processing techniques in order to assess the expected behavior of the user. However, research shows that it is important to also determine the *meaning* of a situation, a step which we refer to as social situation comprehension. We propose using psychological characteristics of situations, which have been proposed in social science for ascribing meaning to situations, as the basis for social situation comprehension. Using data from user studies, we evaluate this proposal from two perspectives. First, from a technical perspective, we show that psychological characteristics of situations can be used as input to predict the priority of social situations, and that psychological characteristics of situations can be predicted from the features of a social situation. Second, we investigate the role of the comprehension step in human-machine meaning making. We show that psychological characteristics can be successfully used as a basis for explanations given to users about the decisions of an agenda management personal assistant agent.

Keywords Personal Assistant Agents · Explainable AI · Social Situation Awareness · Psychological Characteristics of Situations · Predictive Models

1 Introduction

Artificial agents that support people in their daily lives – such as personal assistants, health coaches, or habit formation support agents – are becoming part of everyday lives (e.g. [Kepuska and Bohouta, 2018, Pinder et al., 2018]). Existing work on personal agents usually focuses on modelling personal characteristics of the user, such as their goals, emotional state, or personal values (e.g. [Kop et al., 2014, Fitzpatrick et al., 2017, Cranefield et al., 2017]). However, research in social science shows that human behavior is not only shaped by a person's state and characteristics, but also by the situation they are in [Lewin, 1939]. This suggests that in order to provide better aligned support, personal agents should take the user's situation into account in determining which support to provide.

In this paper we address this challenge, with a specific focus on the *social* dimension of situations. This is important because our daily situations often have a social nature: we spend time at work with colleagues, and free time with

family and friends. Support agents thus need to account for the social dimension of situations, and how that affects the behavior of users. The need for enabling support agents to understand the social situation of the user has been acknowledged as an important open question in agent research [Tambe, 2008, Van Riemsdijk et al., 2015].

Existing approaches (e.g., [Kola et al., 2020b, Dignum and Dignum, 2014, Ajmeri et al., 2017]) tackle this challenge by using some type of situation cues as input (e.g., actors, relationship characteristics, etc.), and using information processing techniques such as machine learning or rule-based approaches to assess expected behavior. By going directly from social situation features to predicted or desired user behavior, the step of understanding the *meaning* of the social situation from the point of view of the user is not performed explicitly. However, research in social psychology (e.g., [Edwards and Templeton, 2005]) suggests that people determine how to behave in a situation by ascribing meaning to this situation, and using this interpretation to decide how to act.

Inspired by this insight, Kola et al. [2021] propose that support agents should perform this step explicitly. They refer to this process as *social situation comprehension*. Following research on situation awareness [Endsley, 1995], they propose a three-level architecture where social situation comprehension is the middle level (Level 2) in between social situation perception (Level 1) and social situation projection (Level 3), as depicted in Figure 1. The idea is that Level 2 information is derived from Level 1 information, i.e., social situation features, and Level 3 information about expected user behavior is in turn derived from Level 2 information.

A central question in realizing such a three-level architecture is in what 'terms' the meaning of a situation should be described. In this paper we investigate whether *psychological characteristics of situations*, a concept used in social psychology (e.g., [Ziegler, 2014, Rauthmann et al., 2014, Parrigon et al., 2017]), can be used for this purpose of achieving social situation comprehension in support agents. The idea behind psychological characteristics of situations is that people view situations as real entities, and ascribe to them traits or characteristics in the same way they ascribe characteristics to other people. These characteristics capture psychologically salient and important meanings [Magnusson, 1977], such as the level of intellect or adversity involved in a situation. An important advantage of using psychological characteristics of situations is that they are general enough to model arbitrary daily life situations [Rauthmann et al., 2014]. This could thus yield flexible personal agents that can handle a wide variety of social situations, which has been proposed as one of the requirements for social situation awareness [Kola et al., 2021].

We investigate the use of psychological characteristics for situation comprehension from two perspectives. First, from a technical perspective we study whether these can be used for predicting user behavior (Level 3 information). Second, we investigate whether they can provide meaningful reasons for explaining the suggestions of the support agent to the user. Research in Explainable AI [Miller, 2019] suggests that explainability of AI systems is important for enhancing their understanding and in turn trustworthiness. Since social science research finds that people determine their actions using situation comprehension, we are interested in finding out whether explicit situation comprehension by a personal support agent can enhance human-machine meaning making.

As in Kola et al. [2019, 2020b], our use case is a calendar management agent for making automated decisions or suggestions to users about how to resolve conflicts in their schedule. We develop computational models that would allow such an agent to assess the priority (Level 3 information) of conflicting meetings, the idea being that the user would attend the one with the highest priority. This is challenging due to the wide variety of social relationships and corresponding social aspects that may go into such decision making. Through this use case, we address the following research hypothesis and questions:

- **RH** Using psychological characteristics of a social situation as input in a machine learning model leads to a more accurate prediction of the priority of the social situation than using social situation features as input.
- **RQ1** To what extent can we use machine learning techniques to predict the psychological characteristics of a social situation using social situation features as input?
- **RQ2** To what extent can we use the predicted psychological characteristics from RQ1 as input in a machine learning model to predict the priority of a social situation?
- **RQ3** To what extent can social situation features and psychological characteristics of situations be used as a basis for explanations that are complete, satisfying, in line with how users reason, and persuasive?
- **RQ4** When do people prefer psychological characteristics of situations in explanations compared to social situation features?

We assess these hypothesis and questions through two studies, one which addresses the technical perspective by creating machine learning models, and one which performs a user study to investigate the use of different kinds of explanations. The rest of the article is organized as follows: Section 2 gives an overview of background concepts that we use throughout the paper. In Section 3 we present our proposed approach for tackling the research questions and hypothesis. Section 4 introduces the first study, presents and discusses its results, and addresses **RH**, **RQ1** and **RQ2**. Section 5

introduces the second study, analyzes and discusses its results, and addresses **RQ3** and **RQ4**. Section 6 concludes the article.

2 Background

This section positions this paper in relation to existing work and offers an overview of background concepts that are used throughout the paper. In particular, we present the three-level social situation awareness architecture proposed in [Kola et al., 2021] which forms the starting point for our work.

2.1 Related Work

Existing approaches for enabling intelligent agents to reason about social context employ some type of social situation information as input, and process that information to assess expected user or agent behavior. For our work we take inspiration from the way in which they conceptualize social situations. The key difference with our work is that we explicitly reason about the meaning of the social situation for the user.

Dignum and Dignum [2014] propose using social practices [Reckwitz, 2002]. Social practices are seen as ways to act in context: once a practice is identified, people use that to determine what action to follow. For instance, the social practice 'going to work' can incorporate the usual means of transport that can be used, timing constraints, weather and traffic conditions, etc. A social practice is identified using information from physical context, social context, activities, etc. Social context includes information about places and roles. Each social practice contains a concrete plan which makes the connection between the social context input and the behavior that needs to be manifested in that situation.

Ajmeri et al. [2017] also highlight the importance of modelling social context in personal agents. Social context includes information such as the place of the interaction or the social relationships between the people in the interaction (i.e., their role). In their approach, the agent includes the social information in the form of norms and sanctions that guide the agent's behavior. These norms and sanctions are formalized as rules in which the social context information serves as the antecedent and the behavior serves as the consequent: the agent exhibits a specific behavior only in presence of specific social context information.

Another approach on how to take into account the effects of social situations on user behavior is proposed by Kola et al. [2020b]. They model social situations through a set of *social situation features* seen from the point of view of the user. For instance, in a situation where a manager and an employee are meeting, the support agent of the employee would model this situation through features such as *setting=work*, *role of other person=manager*, *hierarchy level=higher* and so on. Different from the previous approaches, in this work the relation between the social situation information and the expected behavior is learned rather than modelled explicitly. The authors show that it is possible to use these social situation features as input to a machine learning model to predict expected behavior such as the priority that people would assign to different social situations.

2.2 Social Situation Awareness in Support Agents

Our work builds on that of Kola et al. [2021], who propose a three-level architecture for social situation awareness in support agents. They define social situation awareness as: "A support agent's ability to perceive the social elements of a situation, to comprehend their meaning, and to infer their effect on the behavior of the user". This definition instantiates Endsley's three-level model of situation awareness [Endsley, 1995], yielding three corresponding levels of social situation awareness: social situation perception, social situation comprehension, and social situation projection. The resulting architecture is shown in Figure 1. The focus of this paper is on the second level.

As can be seen from Figure 1, one of the key parts of situation comprehension is the ability to use Level 1 information for deriving a situation profile at Level 2. A situation profile is intended to express the meaning of the situation for the user. Level 1 information concerns features that describe salient aspects of the social situation. This information can come via sensory input or interaction with the user.

Kola et al. [2019, 2020b] propose a set of features based on research from social sciences. They divide features into situation cues, namely *setting, event frequency, initiator, help dynamic*, and social background features describing the social relation between the user and other people in the social situation, namely *role, hierarchy level, contact frequency, geographical distance, years known, relationship quality, depth of acquaintance, formality level and shared interests.* In the rest of this paper we refer to these features as *social situation features* or *Level 1 information*.

The idea is that Level 1 information can be used to infer the meaning of the situation for the user, i.e., Level 2 information. In this paper we investigate the use of psychological characteristics of situations to model Level 2. As proposed in

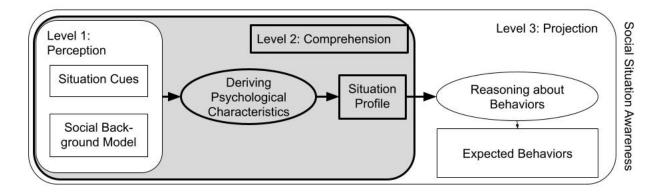


Figure 1: Simplified version of the three-level architecture for Social Situation Awareness proposed by Kola et al. [2021] (emphasis on Level 2 added by us).

social science research, psychological characteristics of situations are used by people to ascribe meaning to a situation [Rauthmann et al., 2014]. People use these psychological characteristics to predict what will happen in a situation, and coordinate their behavior accordingly. There are five main taxonomies which provide a set of psychological characteristics to describe situations [Rauthmann et al., 2014, Parrigon et al., 2017, Brown et al., 2015, Ziegler, 2014, Gerpott et al., 2018], and in this work we use the psychological characteristics proposed in the DIAMONDS taxonomy [Rauthmann et al., 2014]. This taxonomy has several advantages. Firstly, it is intended to cover arbitrary situations, and it offers a validated scale for measuring psychological characteristics. Furthermore, it is shown that the psychological characteristics of a situation correlate both with the features of that situation and with the behavior people exhibit in that situation. The DIAMONDS taxonomy suggests that each situation can be described based on how characteristic each of the following concepts is:

- **Duty** situations where a job has to be done, minor details are important, and rational thinking is called for;
- Intellect situations that afford an opportunity to demonstrate intellectual capacity;
- Adversity situations where you or someone else are (potentially) being criticized, blamed, or under threat;
- Mating situations where potential romantic partners are present, and physical attractiveness is relevant;
- **pOsitivity** playful and enjoyable situations, which are simple and clear-cut;
- Negativity stressful, frustrating, and anxiety-inducing situations;
- Deception situations where someone might be deceitful. These situations may cause feelings of hostility;
- **Sociality** situations where social interaction is possible, and close personal relationships are present or have the potential to develop.

We call such a description a situation profile. In the rest of this paper we also refer to the psychological characteristics of situations as *Level 2 information*.

The idea is then that a situation profile can be used by a support agent to determine expected behaviors for the user (*Level 3 information*), since research on the DIAMONDS model shows that there is a correlation between psychological characteristics of a situation and people's behavior in that situation. Information about expected behavior can in turn be used to determine how best to support the user.

3 Proposed Approach

In this section we present an overview of the approach we take to investigate our hypothesis and research questions. First we present our use case, and then we describe the two studies we performed to investigate the role of situation comprehension in social situation awareness, from a technical perspective (Study 1) and for human-machine meaning making (Study 2).

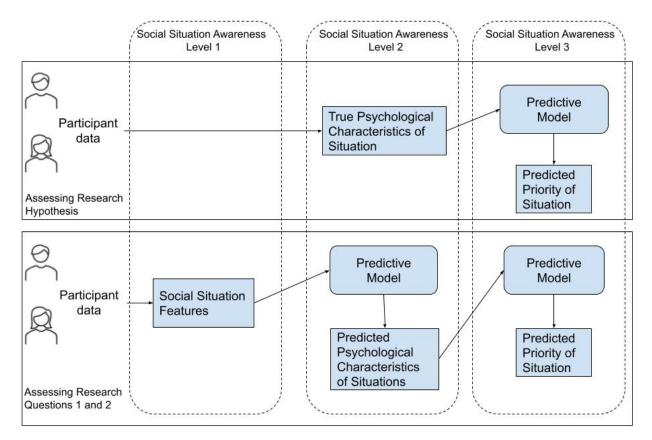


Figure 2: Conceptualization of Study 1, used to assess the research hypothesis (top part), and Research Questions 1 and 2 (bottom part)

3.1 Use case

To perform our research, we need to instantiate the generic social situation awareness model through a concrete use case. In this paper we take the example of a socially aware personal assistant agent which supports users in managing their agenda, inspired by the work of Kola et al. [2020b]. Making accurate predictions on which to base its suggestions and giving insightful explanations is crucial for this agent, making it a good case for assessing our research questions and hypothesis.

An important aspect of agenda management is dealing with scheduling conflicts where not all desired meetings can be attended. We develop predictive models that would allow such an agent to determine the priority level of each meeting, taking into account its social aspects. This is done via determining the situation profile of each meeting consisting of the DIAMONDS dimensions. For example, dinner with a friend might be characterized by a low level of duty, but high level of positivity and sociality, while a meeting with a difficult colleague at work might be characterized by a high level of duty, high use of intellect and high level of adversity, but low level of mating. This information is used to determine the priority level of each meeting, which is expected to correspond with the user behavior (Level 3) of choosing a high priority meeting in case of scheduling conflicts. The agent would make a suggestion to the user about which meeting to attend. Since we use explainable techniques for creating the predictive models, this also allows to determine which features were the most salient in determining the priority. These can be presented to the user as explanations. Following the previous example, if the two meetings are overlapping the predictive model might determine that the second meeting is more important and that the most salient feature is duty. In that case, the agent would tell the user '*You should attend the second meeting since it involves a higher level of duty, and meetings with higher level of duty are usually prioritized*'.

3.2 Study 1: predictive role of psychological characteristics

In the first study we investigate to what extent psychological characteristics of situations can be used for predicting priority of meetings. Following the architecture in Figure 1, a situation profile (Level 2) should be derived from Level 1

information, and it should be able to predict Level 3 information. In order to create corresponding predictive models, we use data from a user study that collects information at Level 1 (social situation features), Level 2 (psychological characteristics) and Level 3 (priority) for a range of meeting scenarios. We then investigate the creation of predictive models in two steps.

First, to assess whether priority could in principle be predicted from psychological characteristics of situations, we take the 'true' Level 2 information as provided by our study participants, and create from this a predictive model for meeting priority (**RH**, top part of Figure 2). While this allows to assess the possibility to predict Level 3 from Level 2, our agent would not have the 'true' Level 2 information since it would be very cumbersome to ask users to provide this information for each meeting. This would not be the case for Level 1 information, since the social relationship features can be collected beforehand and tend to stay stable across situations. Thus we want to investigate (see bottom part of Figure 2) whether we can predict Level 2 information from Level 1 (**RQ1**), and in turn, use these predicted psychological characteristics as input to predict Level 3 information (**RQ2**) using the predictive model that was built to assess our **RH**. This can then be compared with a model that predicts priority directly from social situation features, without the intermediate step of deriving a situation profile [Kola et al., 2020b].

3.3 Study 2: evaluating explanations

In our second study we investigate whether psychological characteristics of situations can be used to provide meaningful explanations to users about the suggestions of the agent about which meeting to attend in case of scheduling conflicts. We assess this by performing two experiments in which we let a hypothetical agent make such a suggestion and provide a corresponding explanation. The agent suggestions as well as the explanations are based on the predictive models that we build in Study 1. We compare Level 2 explanations with explanations that use Level 1 information (social situation features) in two ways.

In the first experiment (between-subject design, **RQ3**, top part of Figure 3), participants are shown either an explanation based on social situation features (Level 1 information), psychological characteristics of the situation (Level 2 information), or a control explanation based on features that were considered not useful. They are asked to rate this explanation on several dimensions such as completeness and persuasiveness. This allows us to assess the suitability of both types of explanations independently. In the second experiment (within-subject design, **RQ4**, bottom part of Figure 3), we show participants both Level 1 and Level 2 explanations for a specific suggestion by the agent, and ask them to *compare* these explanations and indicate which one they prefer. This allows us to assess if there are situations in which one type of explanation is preferred over the other, even in cases where both explanations are considered suitable. If such preferences are found, this can be an indication that a support agent would need to adapt the type of explanations it provides accordingly.

4 Study 1 - Predictive role of Psychological Characteristics

Through this study we evaluate our research hypothesis (RH), as well as RQ1 and RQ2, as shown in Figure 2.

4.1 Method

In this study¹, subjects were presented with meeting scenarios with people from their social circle (Level 1 information) and were asked to rate the psychological characteristics (Level 2 information) and priority of the meetings (Level 3 information). The data that we use for building the predictive models was collected through the experiment described in Kola et al. [2020b]. The experiment was approved by the ethics committee of the university. In their study, Kola et al. [2020b] use only part of the collected dataset which involves the social situation features (see Section 2.2) and the priority of hypothetical social situations. In this work we also make use of information about the psychological characteristics of each of the hypothetical social situations. In this section we briefly describe the method used to collect the data. For more details on the selection of concepts and methods we refer to the description in Kola et al. [2020b].

4.1.1 Material

Social situation features used in the study were based on literature from social science (see Section 2.2 and [Kola et al., 2020b]). Specifically, the features used were: role of the other person, their hierarchy level, the quality of their relationship, the contact frequency, how long they have known each other, the geographical distance, the depth of acquaintance, the level of formality of the relationship, and the amount of shared interests.

¹The survey questions, the data and the source code can be accessed in the supplementary materials in https://doi.org/10.4121/16803889.

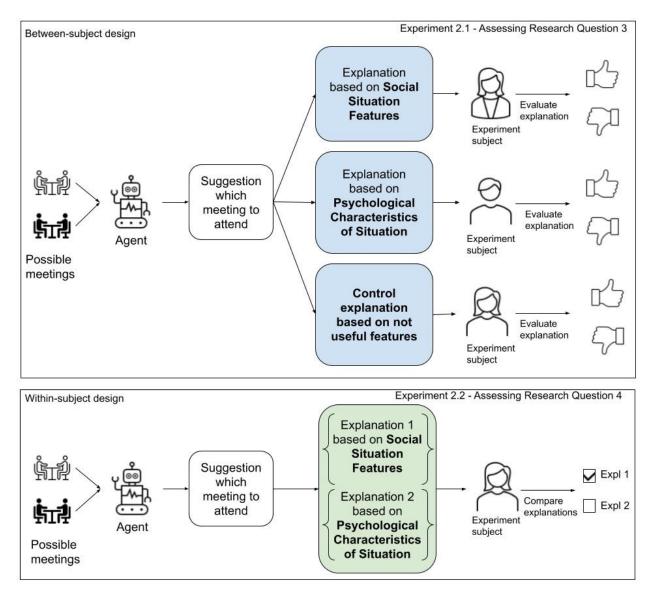


Figure 3: Conceptualization of Study 2, used to assess Research Questions 3 (top part) and 4 (bottom part).

Psychological characteristics of situations were taken from the DIAMONDS taxonomy (see Section 2.2), namely Duty, Intellect, Adversity, Mating, Positivity, Negativity, Deception and Sociality.

Scenarios used in this work represent social meeting settings that a user might encounter in their daily life. The scenarios had a hypothetical nature. Using hypothetical situations gives control over the types of situations subjects are presented with, ensuring a wide variety. To make these hypothetical situations more realistic, subjects were presented with activities that are common for people in their daily lives. Meeting situations were based on inputs from the users of a pre-study, and were formed as a combination of situation specific features (see Section 2.2): setting in which the meeting is taking place, frequency of meeting, initiator, and whether the user is expected to give or receive help (E.g. "You have a weekly meeting with AB^2 where you expect to get feedback on a project that you are working on."). In the situation descriptions, the setting was represented through typical activities that take places within that setting, to make the scenarios more concrete. For instance, the settings 'work' and 'casual' were represented by activities such as 'having a meeting with the supervisor' and 'going for dinner with a friend' respectively.

²For privacy reasons, users only provided only the initials of people from their social circles.

4.1.2 Participants

The study involved 278 subjects recruited through the crowd-sourcing platform Prolific Academic. Of them, 149 were female, 127 were male, and 2 subjects selected the option 'other'. The mean age was 36.2, with a standard deviation of 12.3.

4.1.3 Procedure

Subjects answered an online survey. First, participants were briefed about the purpose of the study. The goal of the study as conveyed to the participants was to collect information about the user's social relationships with different people from their social circle, as well as information about social situations involving the user and those people. Then they were presented with the two parts of the study.

In the first part, subjects were asked to select five people from their social circle, and then were asked questions about their relationship with these people using the set of relationship specific features (see Section 4.1.1). In the second part, subjects were presented with eight hypothetical social situations (see Section 4.1.1), which were meeting scenarios between them and one of the people that they mentioned in the first part of the study (selected randomly). Subjects were asked what priority they would assign to each situation on a 7-point Likert scale (ranging from Very Low to Very High).

Furthermore, subjects were asked about the psychological characteristics of each social situation using the dimensions proposed in the DIAMONDS taxonomy [Rauthmann et al., 2014] (see Section 4.1.1). Subjects were presented with a description of each psychological characteristic, and they were asked "How characteristic are each of the following concepts for this situation?". Subjects answered on a 6-point Likert scale, ranging from Very Uncharacteristic to Very Characteristic.

In total, the dataset consists of information about 1390 social relationships between the subjects and people from their social circle, and about the priority level and psychological characteristics of 2224 hypothetical social situations involving the subjects and one of these people.

4.2 Results

The collected data is used to build predictive models which will be presented and evaluated in this section.

4.2.1 Using Psychological Characteristics of Situations to Predict the Priority of Social Situations

The task of predicting the priority of social situations was previously explored by Kola et al. [2020b]. In their work, they tested different learning algorithms that took as input the features of a social situation to predict the priority of that situation. If we refer to the social situation awareness architecture, this work takes as input Level 1 information and predicts Level 3 information. The best performing model was random forest, which led to a mean absolute error of 1.35, on a 7-points Likert scale.

For this reason, we also employ a random forest model for predicting priority. In our case, the model takes as input the psychological characteristics of a social situation (Level 2), as obtained via the procedure described in the previous section, and predicts the priority of that social situation (as shown in Figure 2, top). Specifically, we use the RandomForestRegressor implementation from the Scikit-learn package in Python. We split the data and randomly assign 80% to the training set and 20% to the test set. We perform parameter tuning by using cross validation on the training set.

The results show that in our model, the mean absolute error is 0.98, which is a significant improvement (Wilcoxon Rank sum test, p < 0.05) over the 1.35 mean absolute error reported by Kola et al. [2020b]. This suggests that psychological characteristics of situations are a better predictor of the priority of social situations than social situation features, thus supporting our hypothesis (**RH**).

4.2.2 Predicting the Psychological Characteristics of Social Situations

The social situation awareness architecture of Kola et al. Kola et al. [2021], says that Level 2 information should be derived from Level 1 information. This is because having the agent ask the users about the psychological characteristics of each situation they encounter would be too invasive and time consuming. On the other hand, collecting Level 1 information can be done more efficiently, since the information about the social relationship can be collected in advance [Kola et al., 2020b]. For this reason, we investigate whether it is possible to predict the psychological characteristics of a social situation using as input social situation features (see Figure 2, bottom).

Since we are dealing with a similar task consisting of the same type of information, we employ again a random forest model which we train on 80% of the data. We built 8 distinct models, where each model predicts one psychological characteristic, since this approach led to better accuracy than having one model that predicts all psychological characteristics at the same time. The model predicts a number from 1 to 6 (on a 6 point Likert scale, 1 being Very uncharacteristics, and 6 being Very characteristic), and the mean absolute errors are reported in Table 1. From the table (column 'Random Forest') we can see that, for instance, the model is on average 1.17 off when predicting the level of Intellect for a social situation. This means that for instance, if the real value is 5 (i.e. Moderately characteristic), the model is expected to predict a value between 3.83 (i.e. Slightly characteristic) and 6 (i.e. Very characteristic).

In order to assess how good these predictions are, we compare our model with a heuristic model that always predicts the mean of the psychological characteristics. The results are reported in Table 1 (column 'Predict Mean'). We see that the random forest model significantly outperforms the heuristic predictor for all psychological characteristics apart from Adversity and Deception. We use a heuristic model for comparison since this is the first benchmark result in predicting the psychological characteristics of a situation. Therefore we do not have an existing baseline to compare it with. Including heuristic baseline predictors is common practice for new machine learning tasks with no predetermined benchmarks (e.g. [Gu et al., 2018]). Kola et al. [2020b] also use heuristic predictors as a baseline for priority prediction, and the most accurate heuristic in that work is an algorithm that always predicts the mean priority.

Table 1: Mean Absolute Errors of the models in predicting the psychological characteristics of situations. Psychological characteristics marked with * represent statistically different results between the two models (Wilcoxon Rank sum test, p < 0.05).

Psychological		
Characteristic	Random Forest	Predict Mean
Duty*	1.34	1.55
Intellect*	1.17	1.3
Adversity	1.29	1.36
Mating*	0.85	1.03
Positivity*	1.14	1.26
Negativity*	1.25	1.37
Deception	1.04	1.09
Sociality*	1.02	1.13

In the next section we evaluate whether these predictions are sufficiently accurate to be used as an intermediate step for predicting priority of social situations. This allows the evaluation of the usefulness this predictive model as part of the bigger social situation awareness architecture.

4.2.3 Predicting Priority through Predicted Psychological Characteristics

To assess the usefulness of these predicted values for predicting the priority of social situations, we predict priority by using as input not the 'true' psychological characteristics of the situation as reported by the participants in the data collection experiment, but the predicted ones (Figure 2, bottom). To do this, we use the model trained in Section 4.2.1, and feed as input the predicted psychological characteristics from Section 4.2.2.

The model achieves a mean absolute error of 1.37 (Table 2). As expected, there is a drop compared to the 0.98 error that we got using as input the true psychological characteristics. Nevertheless, we notice that the prediction error is not significantly worse than the results reported in Kola et al. [2020b], despite using predicted values as input (**RQ2**). This confirms the predictive potential of the psychological characteristics of situations. However, it also suggests the need for more research towards predicting these psychological characteristics more accurately, since that would lead to an overall better prediction of the priority of social situations.

Table 2: Mean Absolute Errors of the models in predicting the priority of social situations when using different inputs. Results marked with * are significantly different from the others (Wilcoxon Rank sum test, p < 0.05).

Model input	Mean Absolute Error in Priority Prediction
Social situation features [Kola et al., 2020b]	1.35
True psychological characteristics of situations	0.98*
Predicted psychological characteristics of situations	1.37

5 Study 2 - Evaluating Explanations

In this section we present the setup of the user study we performed to evaluate explanations given by a hypothetical personal assistant agent about why they suggest attending a specific meeting, based on Level 1 and Level 2 information (**RQ3** and **RQ4**).

In this study³, subjects were presented with pairs of social situations (in this case, meetings), and suggestions from a personal assistant agent regarding which meeting to attend, followed by an explanation that included as a reason either Level 1 or Level 2 information. Subjects were asked to evaluate these explanations (Figure 3). The results of this study are presented in the next section.

5.1 Design Choices and Material

In this section we present the choices we made in the design of the experiment, and the resulting material used for conducting it.

5.1.1 Simplifications

This study falls under the human grounded evaluation category proposed by Doshi-Velez and Kim [2017]: a study with real humans, and a simplified task. The first simplification we made had to do with the fact that subjects were presented with a hypothetical user, i.e., someone other than themselves, and had to evaluate possible explanations given by a hypothetical agent. This simplification was necessary since we do not yet have a fully fledged support agent ready to use and be tested in practice. Studies like these form the foundations needed for creating such an agent. The second simplification had to do with the fact that the explanations were not formed using a specific explainable AI method, but designed by the researchers based on insights from our predictive models in Section 4.2.

In order to make the hypothetical setting as realistic as possible, scenarios were retrieved from the the data collected by Kola et al. [2020a]. In that study, subjects described social situations from their lives, and answered questions about the psychological characteristics of those situations (Level 2). However, the dataset did not include annotated Level 1 information, which is needed to form the explanations based on this type of information. To perform the annotation, we used information that is available in the description of the situations. For instance, if the description says 'I am meeting my boss to discuss the project', we infer that the role of the other person is *supervisor*, the hierarchy level is *higher* and the setting is *work*, and consider the information that is not available in the description to be equal across situations. Using only explicit information available in the description to infer Level 1 information allows this procedure to be unambiguous. At this point, we have a dataset with situations described by people, annotated in terms of their social situation features and psychological characteristics which will be used to form the explanations.

5.1.2 Selecting which information is included in explanations

For an explanation to be realistic, it needs to be based on information that contributed to the suggestion of the agent. In order to find the Level 1 and Level 2 information that is more likely to have contributed to the priority prediction, we identified the features that have the highest weight when predicting the priority of social situations using the TreeExplainer method of the SHAP package [Lundberg and Lee, 2017]. For Level 1, these features were setting, help dynamic, role, relationship quality, age difference, and shared interests. For Level 2, these features were duty, intellect, positivity and negativity. We assume that the best explanation can be found in this pool of features, since they are the best predictors of priority.

5.1.3 Selecting scenarios

We want users to evaluate the type of information included in the explanations, rather than evaluate whether the agent selected the right feature to include in the explanation. To facilitate this, we formed pairs of scenarios in such a way that both meetings have a set of common situation features/psychological characteristics and a single differing one, which would then be used in the explanation. This was done using the following procedure:

- *Level 1* Each meeting is annotated with a set of social situation features. To form pairs, we selected scenarios that have the same amount of information in terms of social relationship features (i.e., same number of social situation features known), and that differ in only one social relationship feature.
- *Level 2* Each meeting is annotated in terms of its psychological characteristics, rated on a scale from 1 (very uncharacteristic of the situation) to 7 (very characteristic of the situation). We consider psychological

³The survey questions and the data can be accessed in the supplementary materials in https://doi.org/10.4121/16803889.

characteristics with a score higher than 4 to have a *high relevance* in the situation, and those with a score lower than 4 to have *low relevance*. To form pairs, we selected scenarios that have a similar level of relevance (i.e., either high or low) for all psychological characteristics except for one, which has a differing level of relevance.

In total we formed eight pairs of scenarios, where the differing social relationship features were setting, help dynamic, role, relationship quality, age difference, and shared interests. The differing psychological characteristics were duty, intellect, positivity and negativity (two pairs for each). For instance, one of the pairs was:

Meeting 1 - Alice has planned to meet a colleague because they want to update each other about their work.

Meeting 2 - Alice has planned to meet another colleague because the colleague needs her help to solve a work task.

In this case the differing social relationship feature was the help dynamic⁴, which was *neither giving nor receiving help* for the first meeting and *giving help* in the second (as inferred from the scenario descriptions), whereas the differing psychological characteristic is the level of duty, which was higher in the second meeting (as annotated by the subjects who proposed these scenarios).

5.1.4 Selecting Agent Suggestions

To determine which meeting the agent should suggest the user to attend, we used a heuristic procedure based on the prediction models from Section 4.2. Through the TreeExplainer method [Lundberg and Lee, 2017] we determined whether each differing feature contributes to a higher or a lower priority level. Since meetings differ in one feature (for each of Level 1 and Level 2), that feature is used as the tie breaker to determine which scenario should have higher priority. Scenarios were selected in such a way that the agent would make the same suggestion regardless whether it uses Level 1 information or Level 2 information for the prediction. This was done to minimize the effect that the agent suggestion has on the evaluation that the subjects give about the explanations. For the aforementioned pair, Meeting 2 has a higher priority because, based on the prediction models:

- Meetings where someone is expected to give help have a higher priority (Level 1 information);
- Meetings with a higher level of duty have a higher priority (Level 2 information).

5.1.5 Selecting explanations

To form the explanations, we followed insights from research on Explainable AI which suggests using shorter explanations that have a comparative nature [Miller, 2019, van der Waa et al., 2021]. For this reason, explanations include only the differing feature between the meetings (one for each explanation), and are phrased as comparisons between the available choices. For the previously introduced pair of scenarios, the explanations would be:

Explanation based on Level 1 information - Alice should attend Meeting 2 because she is expected to give help, while in Meeting 1 she isn't, and meetings where one is expected to give help are usually prioritized.

Explanation based on Level 2 information - Alice should attend Meeting 2 because because it involves a higher level of duty, which means she is counted on to do something, and meetings involving a higher level of duty are usually prioritized.

5.2 Measurement

In order to evaluate how good the explanations are, we first need to decide on a set of criteria based on which they can be evaluated. Vasilyeva et al. suggest that the goal of the explainer is key in how the explanations are evaluated. Different goals of explainable systems identified in the literature are transparency, scrutability, trust, persuasiveness, effectiveness, education, satisfaction, efficiency and debugging [Chromik and Schuessler, 2020, Tintarev and Masthoff, 2012, Wang et al., 2019]. In our setting, the objective of the personal assistant agent is to justify its suggestions so the user can decide to accept them or not. Therefore, its main goal is to offer clear and understandable explanations for the reasons behind the suggestion, which relate to the goals transparency and satisfaction. Furthermore, we want to assess the persuasive power of the explanations.

To assess how clear the explanations are, we use an adapted version of the explanation satisfaction scale [Hoffman et al., 2018]. From the scale, we use the following statements:

⁴The feature *help dynamic* can take the values *giving help, receiving help, neither giving nor receiving help.*

- The explanation of [...] is *satisfying*;
- The explanation of [...] has *sufficient detail*;
- The explanation of [...] seems *complete*;

We do not include the items of the scale that refer to accuracy, trust, usefulness to goals and whether the explanation tells the user how to use the system, since these items are not related to the goals of the envisioned support agent.

To further inquire about the clarity and understandability of the explanations, we add the following statement:

• The explanation of [...] is in line with what you consider when making similar decisions;

This is done because we expect that being presented with information which is similar to what they consider when making similar decisions would make the explanations more understandable for the user.

Lastly, another goal of the agent is persuasiveness, which means how likely are the explanations to convince the user to follow the suggestion. This was captured through the following question:

• The explanation of [...] is likely to convince Alice to accept the suggestion.

These items were rated on 5-points scales which were different for each experimental setting, as specified in Section 5.4.1 and Section 5.4.2.

5.3 Participants

In total, we recruited 290 subjects through the crowd-sourcing platform Prolific Academic. Participation was open to members that had listed English as their first language. Every subject was compensated for the time they spent completing the study, as per the guidelines of the platform. The study consisted of two experiments. For the first experiment we recruited 100 subjects. Of these, 55 were female, and 45 were male, with a mean age of 31.1 and a standard deviation of 11.8. For the second experiment we recruited 190 subjects. Of these, 108 were female, 80 were male, 1 selected the option 'other', and 1 selected the option 'prefer not to say'. They had a mean age of 29.98 with a standard deviation of 10.28.

5.4 Procedure

In this section we introduce the procedure that was used for this study. The study consisted of two experiments. In Experiment 2.1 we address **RQ3**, while in Experiment 2.2 we address **RQ4**. Both experiments were conducted as online surveys, and the subjects were recruited through the crowd-sourcing platform Prolific Academic. The study received the approval of the ethics committee of the university. The experimental procedure was similar in both experiments:

- Introduction Subjects were informed about the study and were presented with the consent form.
- *Demographics* Subjects were asked about their age and gender to check whether the population sample was sufficiently broad.
- *Case-study* Subjects were introduced to Alice, a hypothetical user of the socially aware personal assistant agent. Subjects were told that during a specific week Alice is particularly busy, so the agent makes suggestions which meetings she should attend and which ones she should cancel.
- *Scenarios* Subjects were presented with a pair of meeting scenarios, and they were asked which meeting they would suggest Alice to attend. This was asked to control for biases that they would have regarding the agent's suggestions, in case their own opinion differed from that of the agent. Furthermore, in an open question they were asked about the reasons behind this suggestion. This was asked to get more insights into the reasoning process of subjects in such situations. In total subjects were presented with four pairs of scenarios.
- *Evaluation of explanations* Subjects that made suggestions in line with the agent were presented with the full questionnaire which included all measures from Section 5.2. Subjects that made suggestions that were different from what the agent would suggest were presented with a question regarding the persuasiveness of the different explanations (namely: "The explanation offers convincing arguments"). This was done to take into account biases: We expect that subjects that do not agree with the agent suggestion would be implicitly evaluating the suggestion rather than its explanation.

In the next subsections we present the specifics of each experiment.

5.4.1 Experiment 2.1

This part of the study had a between-subjects design. Subjects were presented either with explanations based on Level 1 information, Level 2 information, or they were part of the control group, which we added to serve as a baseline. In related work (e.g., [van der Waa et al., 2021]), control groups normally do not include an explanation, since the goal is usually to evaluate the impact of the explanation in the overall quality of the suggestion. However, in our setting that would be obsolete since the questions specifically refer to explanations. For this reason, in the control group subjects were presented with explanations that included information that could in principle be useful for determining the priority of meetings, but did not make sense for those specific scenarios. Explanations in the control group included information such as weather, geographical location or time. For instance, an explanation was "Alice should attend the first meeting because it is spring".

This design presents subjects with only one type of explanation, so the evaluation is absolute rather than relative to the other explanation types. This allows us to answer **RQ3**: to what extent can social situation features and psychological characteristics of situations be used as a basis for explanations?

The aforementioned measurements were presented as statements such as "The explanation provided about the reasons why the agent suggests Meeting 2 is satisfying". Subjects could answer on a 5-point Likert scale, ranging from Strongly disagree to Strongly agree.

5.4.2 Experiment 2.2

This part of the study had a comparative within-subject design. This design presents subjects with two explanations for each pair of scenarios: one based on Level 1 information, and one based on Level 2 information. Through this setting, we address **RQ4**: when do people prefer one type of explanation versus the other? The measurements were framed as comparisons, for instance "Which explanation do you consider more satisfying?". Subjects could answer 'Significantly more Explanation A', 'Slightly more Explanation A', 'Both equally', 'Slightly more Explanation B' and 'Significantly more Explanation B'.

5.5 Results and discussion

In this section we present the quantitative results of the two user studies described above, and we analyze the answers to the open question.

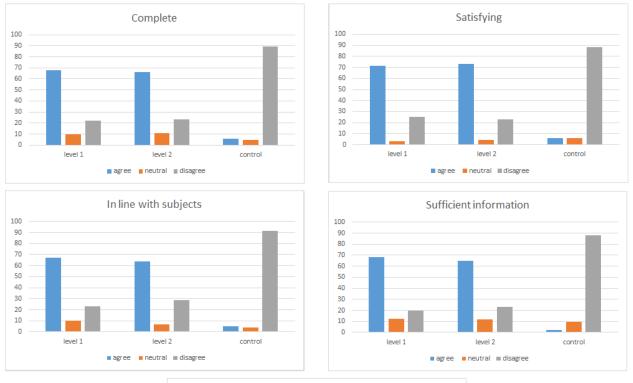
5.5.1 Experiment 2.1

Each of the subjects was presented with four pairs of scenarios, which means 400 pairs of scenarios were shown to subjects across the different conditions (128 pairs in the Level 1 group, 140 pairs in the Level 2 group, and 132 pairs in the control group). In 73% of the total cases, subjects would suggest Alice to attend the same meeting that the agent would suggest. Figure 4 presents the subjects' answers for each of the measurements regarding the explanation provided by the agent. This applies to the subjects whose suggestions were in line with the suggestions of the agent. The majority of the subjects considered the explanations based on Level 1 or Level 2 information to be complete, satisfying, in line with how the subjects reason, likely to convince the user, and having sufficient information. The distribution of answers for Level 1 and Level 2 are not statistically different (Wilcoxon Rank sum test, p > 0.05).

While explanations based on Level 1 or Level 2 information were thus considered positively, on the other hand, subjects strongly disliked the explanations offered in the control setting. This confirms that the positive effect was not just due to the presence of an explanation as such, since subjects do not give a positive evaluation to an explanation which does not apply to the suggestion.

The answers of the subjects whose suggestions were not in line with the suggestion of the agent are presented in Figure 5. We see that subjects do not find the explanations of the agent to provide convincing arguments. This shows that there is some inherent bias, and that subjects are implicitly evaluate the quality of the suggestion too, and not just the explanations. However, we notice that explanations containing Level 2 information are still seen as convincing in 40% of the cases, compared to 21.6% for explanations containing Level 1 information.

This experiment allows us to answer **RQ3**: Approximately 70% of the subjects find the explanations based on Level 1 or Level 2 information to be complete, satisfying, in line with the way the subjects reason, likely to convince the user, as well as containing sufficient information. This makes such information a good candidate for forming explanations in personal assistant agents.



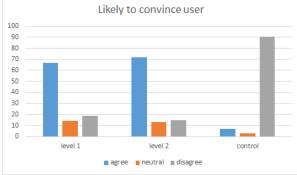


Figure 4: Answer distributions for the different measurements. The x axis represents the answer options for each of the levels. 'Strongly agree' and 'Somewhat agree' were grouped together as 'agree', and 'Strongly disagree' and 'Somewhat disagree' were grouped together as 'disagree'. The y axis shows the percentage of subjects that gave a specific answer.

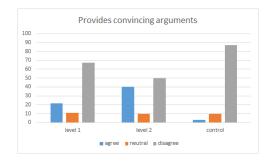


Figure 5: Answer distribution for the subjects who would make a suggestion different from the agent's.

5.5.2 Experiment 2.2

The goal of Experiment 2.2 was to evaluate **RQ4**. Results are presented in Figure 6. It shows the results for each of the 8 pairs of scenarios, mentioning which Level 1 and Level 2 feature were used for the explanations.

The results show that the preferences of the subjects vary between pairs. However, we notice consistency within the pairs: for a specific pair, subjects tend to prefer the same explanation across all measurements. Given this, for simplicity we will abuse terminology and say that subjects prefer one explanation over the other in a pair of scenarios when the subjects prefer that explanation for at least five of the six total measurements.

We can see that in situations where duty is the salient feature (Pairs 1 and 2), subjects prefer explanations involving Level 2 information. On the other hand, in situations where negativity is the salient feature (Pairs 5 and 6), subjects strongly prefer explanations involving Level 1 information. This seems to suggest that subjects do not like explanations that have a negative framing⁵. For situations where the salient feature is intellect or positivity we cannot reach a clear conclusion regarding which explanation is preferred, since the results are different across pairs and seem to be context dependent.

This experiment gives some insights towards answering **RQ4**. It shows that subjects prefer explanations involving Level 2 information when duty is the salient feature, and explanations involving Level 1 information when negativity is the salient feature. However, this experiment also shows that more research is needed to determine which type of explanation is preferred for each situation. Overall, an agent that can give explanations including information from either level is beneficial, since the preferred explanation is context dependent and can vary.

5.5.3 Open question analysis

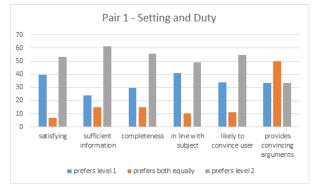
After answering which meeting they would suggest to Alice, subjects were also asked about the reasons behind this suggestion. This was done to assess the type of information that users would include in their reasoning, and how it compares to the explanations given by the agent. The results are presented in Figure 7. The answers were analyzed by the first author in a two step procedure: first each open answer was annotated whether it contains Level 1 information, Level 2 information or neither, and secondly, answers which included neither were annotated and clustered based on their content.

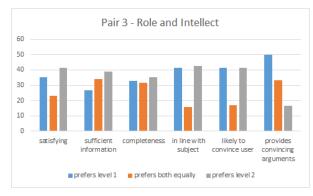
The results show that in more than half of the cases, subjects offered a reason that involved either the Level 1 or the Level 2 relevant feature for that pair. This confirms that subjects also reason themselves in terms of this information in many cases. Level 1 information was mentioned significantly more than Level 2 information, but this was to be expected since Level 1 information is directly present in the description of the meetings, so it is more salient.

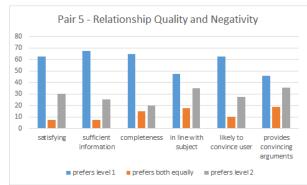
From this open question we can also extract other types of information that users find relevant. For instance, in 12% of the cases subjects gave a reason that was related to temporal aspects, such as 'Meeting 1 is more urgent', or 'Meeting 2 is more difficult to reschedule'. This feature should be considered for inclusion to the list of Level 1 situation features, since it was consistently mentioned by subjects. Two other reasons that were consistently mentioned were 'more beneficial' and 'more important'. Subjects also mentioned various other similarly vague answers (e.g. 'better') which did not appear consistently, therefore were clustered under 'other'. Such answers show that subjects often do not explicitly dig deeper into the reasons, but offer only superficial ones.

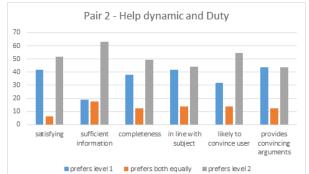
When taking a closer look at subjects who in the open question used Level 1 or Level 2 information, we notice that the reasons that the subjects give do not necessarily match with their preferred explanations. In 43% of the cases, in the open question subjects gave as a reason for their suggestion information from one of the levels, and in the questionnaire they preferred the explanation that included information from the other level. For instance, in the open question for Pair 5 one of the subjects says "*Meeting two will be more enjoyable and less stressful*", which fits almost perfectly with the explanation given by the agent that involves Level 2 information. However, in the questionnaire this subject always prefers significantly more the explanation that includes Level 1 information. This 'flip' happens in both directions: in 50% of cases it's from Level 1 to Level 2 and in 50% the other way around. This suggests that there are users that want to hear explanations that differ from the reasons that they thought about themselves, providing another perspective on which explanations the agent should provide to the user.

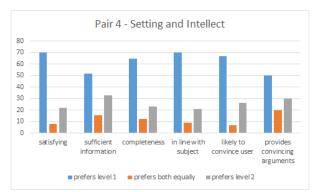
⁵The explanation involving Level 1 information was "Alice should attend Meeting 2, since in it she is meeting someone with whom she has a better relationship, and meeting with people with whom one has a better relationship are usually prioritized.", while the explanation involving Level 2 information was "Alice should attend Meeting 2, since Meeting 1 could entail a high level of stress, and meetings that entail a low level of stress are usually prioritized."

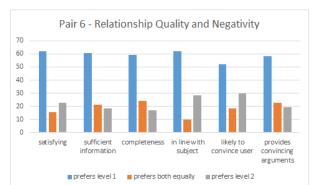












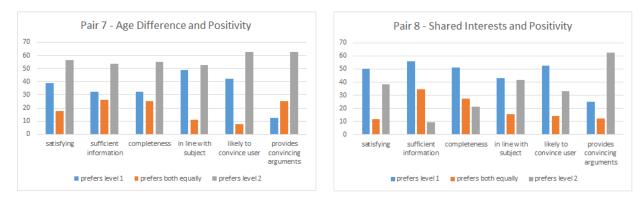


Figure 6: Answer distributions for each of the pairs in Experiment 2.2. Each graph shows the preferred type of explanation for the different evaluation metrics.

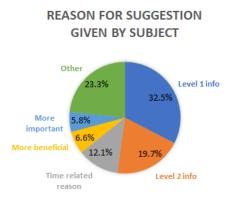


Figure 7: Distribution of reasons given by the subjects when asked why they would suggest attending a specific meeting.

6 Conclusions

6.1 Contributions

In this work, we investigate the use of psychological characteristics of situations as a central concept for achieving social situation comprehension in support agents. Social situation comprehension is the middle level of the three-level social situation awareness architecture proposed by Kola et al. [2021]. As such, it should be assessed according to its function in this architecture, i.e., being predicted from information obtained through social situation perception, and allowing the prediction of the information needed for social situation projection. Furthermore, we have suggested that situation comprehension could not only be used by the agent itself to interpret a situation, but could also have a function in human-machine meaning making: if people interpret situations in terms of psychological characteristics, then its use in human-machine interaction may enhance how user and machine together understand the situation. We specifically investigated this through the use of psychological characteristics in explanations for the agent's suggestions.

First of all, we show that psychological characteristics of situations are a significantly better predictor of the priority of situations than social situation features, thus supporting our hypothesis (**RH**). This suggests there can be benefits of having explicit social situation comprehension in support agents in terms of its prediction accuracy.

Furthermore, we show that it is possible to predict the psychological characteristics of a situation using a random forest model which takes as input the features of that social situation (**RQ1**). When using the predicted values as input to predict the priority of the situation, there is a drop in accuracy (**RQ2**). However, despite using as input predicted values the prediction error is not worse than the one reported in related work which goes directly from social situation features to priority.

Lastly, we show that people find explanations based on social situation features and psychological characteristics of situations to be satisfying, containing sufficient information, complete, in line with how they think, and convincing (**RQ3**). People prefer explanations based on psychological characteristics in situations where the level of duty is relevant, and explanations based on social situation features in situations where the level of negativity is relevant (**RQ4**). Overall, both types of explanations were evaluated positively, indicating that it may be beneficial if support agents were able to give explanations based on both types of information.

Overall, our results suggest that psychological characteristics of situations can be a central concept for social situation comprehension in support agents, having both technical benefits and benefits for situation comprehension between user and support agent.

6.2 Ethical impact

Several ethical considerations have to be made before deploying an agent with a social situation comprehension module to offer support in the real world. First of all, the agent's assessments of the priority of situations can be mistaken, thus offering to the user suggestions that can have social repercussions. For this reason, in our use case the decision remains in the hands of the user, and the agent also offers explanations for its suggestions. However, this also does not fully mitigate ethical risks. For instance, the agent might wrongly infer that a specific social situation has a high level of negativity, and inform the user about it in an explanation. However, if this is a situation which is sensitive for the user,

the explanation can cause distress. Therefore, it is important to increase prediction accuracy, as well as to have more studies that assess the effects on a user of using such an agent on a daily basis.

6.3 Limitations and Future Work

In this work, results were based on the use case of a socially aware personal assistant agent. Future work should extend the findings for different types of support and other support domains. Here it will be particularly interesting to investigate if the generality of psychological characteristics makes them a good candidate to predict other aspects of social situations besides their priority. Assuming a support agent that can assist in various tasks and different daily situations, having a common conceptual grounding for assessing the meaning of situations for the user could have advantages for human-machine meaning. Furthermore, in this paper we used a hypothetical setting in order to be able to gather larger amounts of data in a controlled way. Based on the results from this hypothetical setting, it is important to build a prototype support agent in order to test the methods in real tasks.

While answering Research Questions 1 and 2 we found that predicting the psychological characteristics of situations accurately is crucial in order to better predict the priority of situations. In future work, we will explore other techniques, such as using natural language processing techniques to extract the psychological characteristics of situations from textual descriptions of situations. Lastly, Study 2 shows that while both social situation features and psychological characteristics of situations can be the basis of explanations given by support agents, more research is needed to determine which type of explanation to give in which situation.

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