Exploring Preferences in Human-Robot Navigation Plan Proposal Representation

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ABSTRACT

In this paper, we present our focus on unraveling the intricacies of plan negotiation in human-robot collaborative navigation (HRCN) through a comprehensive exploration of human preferences over robot proposals in search tasks. Via online survey data, we explore the multidimensional landscape of diverse plan representations, negotiation contexts and negotiation domains. Our study seeks to identify the crucial factors that exert a significant influence over human perception, shedding light on the dynamic interplay between humans and robots and contributing valuable insights to advance the understanding of effective navigation plan negotiation strategies in human-robot teams (HRT).

CCS CONCEPTS

• Computer systems organization → External interfaces for robotics; **• Human-centered computing → User studies**; **Collaborative interaction**; **• Information systems → Collaborative search**; **Task models** .

KEYWORDS

plan negotiation; human-robot negotiation; human-robot collaborative navigation; human-robot collaborative search; task allocation

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1 INTRODUCTION

Plan negotiation between humans and robots can enhance efficiency, leverage teammates' unshared knowledge, and expand potential outcomes. However, this comes at the cost of heightened complexity in plan creation and assessment. This study delves into human preferences in negotiating plans within human-robot teams engaged in collaborative navigation tasks, specifically search tasks, utilizing data from online surveys. Our investigation focuses on examining various plan representations, negotiation contexts, and negotiation domains within the realm of robot-to-human navigation plan proposals. Our goal is to build useful knowledge to be able to make an informed decision when choosing a plan representation to deliver robot proposals in plan negotiation models.

Some systems handling human-robot teams include verbal communication at the task planning level [1, 6, 8], contemplate robot agents capable of requesting the usage of a resource from a human manager [2], generate plan proposals for navigation tasks dynamically adapting to new human preferences [4] or ask for assistance when needed [3]. Interestingly, Moon et al. [5] explore the implicit negotiation domain of hesitation trajectories to enable human-robot non-verbal negotiation and Porteous et al. [7] study human understanding of robot intentions upon graphical robot plan representations. Nevertheless, to our knowledge, none of them confront explicit human-robot negotiation scenarios where both humans and robots are capable of proposing and agreeing on plans.

Motivated by this gap, our study contributes to HRI knowledge, examining nuanced human preferences in HRT navigation plan negotiation. Specifically, we investigate the influence of diverse representations and negotiation domains in involved humans, providing insights for designing user-centric, adaptable robotic systems.

We provide task and proposal definitions for two different navigation plan negotiation domains in Section 2 and concretize this definition applied to our use case, robot proposals in search tasks, in Section 3. Then, we present the data collection approach of our study in Section 4 and discuss the obtained results in Section 5.

2 NAVIGATION PLAN PROPOSAL

Consider a human-robot team (HRT) confronted by a known collaborative navigation task. The team objective is to construct and agree on a complete or partial plan to tackle this task. We define negotiation as the plan-building process encompassing from the collaborative task declaration to the reachment of either an agreement or the occurrence of a withdrawal.

The team reaches an agreement when all members accept a mutually known plan proposal ω. This acceptance can be delivered either explicitly, conveying a confirmation message, or implicitly. The latter being considered only if all team members execute a commonly known plan. Taking action without a commonly known plan or not receiving acceptance from all team members is considered a withdrawal.

2.1 Task Definition

A collaborative navigation task T is a task given to a set of agents $\Lambda = \{a_i | i = 1...m\}$. Generally, each agent may internally perceive T as formed by a set of subtasks. Each sub-task γ might be assigned to a non-empty set of target agents $\tau \subseteq \Lambda$. One might refer to a sub-task as γ if it is assigned to all team members. Otherwise, it should be referred to as γ^{τ}. Thus, generally:

$$T = \{\gamma_1, ..., \gamma_n\}, \quad T^{\Lambda} = \{\gamma_1^{\tau_1}, ..., \gamma_n^{\tau_n}\} \tag{1}$$

Note that having multiple targets (assigned agents) does not imply they should all do the sub-task, but that any of them can fulfil it. Also, note that sub-task granularity is not necessarily specified with the task and, thus, it is possibly different for each agent.

Additionally, in certain scenarios sub-tasks may have time window constraints C. Any constraint $c \in C$ is defined as an interdependence relation between two sub-tasks $c(\gamma_p, \gamma_q)$. All constraints may be represented in a directed graph $G_T = (T, C)$.

2.2 Plan Proposal Domains

The team objective in navigation plan negotiation is to construct and agree on a complete or partial plan proposal $\omega \in \Omega$ to tackle a collaborative navigation task T, being Ω the set of possible proposals of the negotiation domain. From now on, we will consider two negotiation domains in navigation task negotiations: navigation plan negotiation and assignation plan negotiation.

2.2.1 *Navigation plan proposal.*

Let proposal ω be a team navigation plan $x \in \mathcal{X}$ constructed by the agents' movements $x = \{x^{a_1}, ..., x^{a_m}\}$, where $\mathcal{X}$ denotes the set of feasible team plans. Then, each agent movement $x^a \in \mathcal{X}^a$ can be defined as an ordered sequence of basic movement actions $x^a = \{x_1^a, x_2^a, ..., x_k^a\}$, being $\mathcal{X}^a$ the possible action sequences of agent a.

Basic movement actions x_i^a are defined by their goal, encoding the action of moving to it. Each x_i^a may have an associated finish time t_i^a only if it has been specified and agreed upon by the team.

2.2.2 *Assignation plan proposal.*

Let proposal ω be an assignation plan $\Gamma = \{\Gamma_1^{\tau_1}, \Gamma_2^{\tau_2}, ..., \Gamma_N^{\tau_N}\}$ where $\Gamma_j^{\tau_j} = \{\gamma_{i_j(1)}^{\tau_j}, ..., \gamma_{i_j(n_j)}^{\tau_j}\}$, $\Gamma_j = \{\gamma_{i_j(1)}, ..., \gamma_{i_j(n_j)}\}$, $i_j(k_j) \in \{1...n\}$ $\forall k_j \in \{1...n_j\}$ and:

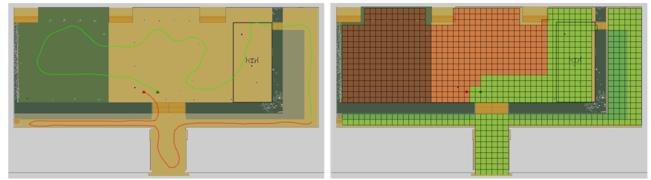

Figure 1: From left to right: a) shows two paths as the navigation plan representation of a selfish plan x. b) shows the assignation plan representation of a balanced plan Γ.

$$\tau_j \subseteq \tau_i \quad \forall i \in \{i | \gamma_i \in \Gamma_j\} \tag{2}$$

$$\bigcup_{j \in N} \Gamma_j = T, \quad \bigcap_{j \in N} \Gamma_j = \emptyset \tag{3}$$

A proposal conveying this kind of information should both identify the sub-task and the proposed assignation change. Subsequently, agents in the team should be able to establish an equivalence relation between the received sub-task sets definition $\Gamma_j^{\tau_j}$ and their own. Generally, this can even demand a change in the receiver task internal representation.

3 USE CASE

Let us consider a HRT of agents Λ tasked with searching for a misplaced object O in a given and known zone. All agents are assumed to have rotational symmetry on detection capabilities.

Regardless of the human's understanding of the task, the robots internally represent it as a set of searching sub-tasks γ_s and a task linked to the object localization event γ_o. All sub-tasks are assumed as initially assigned to both team members and all γ_s have a soft precedence constraint [4] related to γ_o, as no γ_s can be fulfilled once γ_o is completed. Formally, having $\tau = \Lambda$:

$$T = \{\gamma_{s_1}^{\tau}, ..., \gamma_{s_n}^{\tau}, \gamma_o^{\tau}\}, \quad G_T = (T, \{sp(\gamma_{s_i}, \gamma_o) | \forall i \in \{1...n\}\}) \tag{4}$$

From the robots perspective, the search space of the navigation task is discretised. We define γ_s as the searching sub-task of the object on a given area A_s resulting from this division (Figure 1.b). One implementation representing this task using the *social reward sources (SRS)* model can be found in [4].

3.1 Robot Proposal Representation

To test the participants' negotiation preferences, we designed three plan representations. Following Section 2.2 taxonomy:

3.1.1 *Navigation plan proposal.*

A visual navigation plan representation (Figure 1.a). This representation represents x as a path plan with actions $x_i^a \in \{x, y\}$ for each agent. No explicit t_i^a is defined.

3.1.2 *Assignation plan proposal.*

Two assignation plan representations for an assignation plan Γ:

A *visual* representation depicting area assignation through grid colouring where each cell j represents $\Gamma_j^{\tau_j}$ (Figure 1.b).

A *verbal* description with each $\Gamma_j^{\tau_j}$ describing broader areas and given by text, but participants are asked to imagine the robot delivers the information through audio. For instance, the balanced plan for contexts 1 and 2 (Section 4) was: *I'll search in the grass and central zones while you search in the bar, gravel and paved zones.*

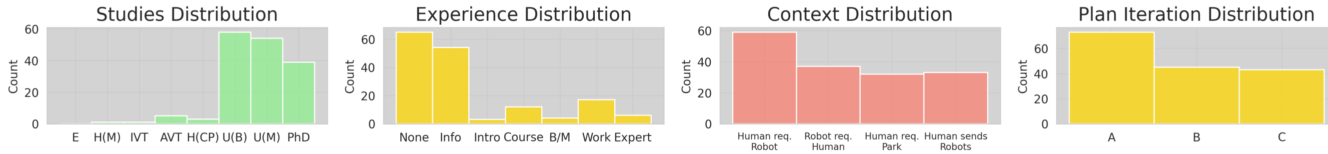

Figure 2: Demography and data distributions

4 DATA COLLECTION

This study has been performed through an online questionnaire. The questionnaire was available in three languages (Catalan, Spanish and English), unicity of participant responses has been ensured and data[1] has been collected from August to October of 2023.

4.1 Participants

A total of 161 volunteers have participated in the study. They were from 20 to 77 years old (mean: 43.13, std:15.35), 91 men, 70 women and none self-identifying otherwise. Demographic data related to studies (finished or ongoing) and experience in robotics can be observed in Figure 2.

4.2 Contexts

Participants in this study were asked to imagine themselves in either a human-robot (hr) search setting or acting as a supervisor in a robot-robot (rr) setting. They where randomly assigned one of the following contexts during the experiment:

Context 1 (c1,hr). You have just realized that you have lost your mobile phone. You approach a service robot working in the park and ask for help in finding it.

Context 2 (c2,hr). While you are in the park, a service robot working there approaches you and asks for help in finding a lost mobile phone. Assume you have the time and agree to help.

Context 3 (c3,rr). When you arrive home, you realize that you have lost your mobile phone at the park. You make a search request to the assistance system, and two park service robots are assigned to your case. Shortly afterwards, you receive a message from one of the two robots.

Context 4 (c4,rr). When you arrive home, you realize that you have lost your mobile phone at the park. However, you have a prior commitment and cannot return to the park in person. So, you send two robots that you have at home to search for it. When they arrive at the park, you receive a message from one of the two robots.

Contexts 1 and 2 were added to study the preference changes caused by the existence or lack of intrinsic motivation of the human, whilst contexts 3 and 4 were proposed to study preference changes due to the perception of property over the robots.

4.3 Plan Combination

To study the possible existence of perception variance caused by plan quality, each participant has been presented with three plans:

Balanced plan (1). Plan where both members of the team take care of similar workload, both in path length and search area.

Selfish plan (2). Plan where the proposing robot takes care of significantly less workload, both in path length and area.

[1]https://www.iri.upc.edu/groups/mobrobotics/pref_in_hrn_plan_prop

Table 1: Robot to Human Plan Representation

Setting	hr						rr					
Context	c1			c2			c3			c4		
Plans	A	B	C	A	B	C	A	B	C	A	B	C
Path	1	2	3	1	2	3	1	2	3	1	2	3
Area	3	1	2	3	1	2	3	1	2	3	1	2
Audio	2	3	1	2	3	1	2	3	1	2	3	1
Option	1	2	3	4	5	6	7	8	9	10	11	12

Selfless plan (3). Plan where the proposing robot takes care of significantly more workload, both in path length and area.

Each participant was presented with one combination of these three plans and three representations. The possible combinations, shown in Table 1, are identified with the labels A, B and C. Applying this to each of the four contexts spawns 12 different questionnaire iterations, from now on options. Each participant only answered to one of these options chosen randomly, though there is a surplus of *option 1* samples due to an initial labelling error (Figure 2).

4.4 Preference Data

For each of the three plan proposal scenarios presented to the participants, they were asked to answer a number of questions related to the quality and perception of the plan (Informative, Intuitive, Clear, Reasonable, Efficient, Logic and Fair) and to robot perception (Leader, Intelligent, Controlling and Collaborative) following 7-item Likert scales. Moreover, at the end of the questionnaire, the participants were asked to rank by order of preference the three plan representation modes (Audio, Area and Path).

5 RESULTS

In the following section, a statistical analysis of the data obtained through the online questionnaire is discussed.

5.1 Preference

Results of the participants' ranking of the plan representation are shown in Figure 3. Its first two graphs present preference ranking over team structure. In the HR search there seems to be a clear ranking preference (*Area* > *Path* > *Audio*), whilst in the RR case area and path representations have no clear ranking difference.

The equality hypothesis is discarded through a Friedman test and one-to-one differences are evaluated through post-hoc tests (Figure 4). Ranking differences over all plan representations are statistically significant in HR settings, whilst the RR table shows that the difference between area and path rankings when the human isn't participating in the search is not statistically significant. We obtain the same results for all contexts of each category.

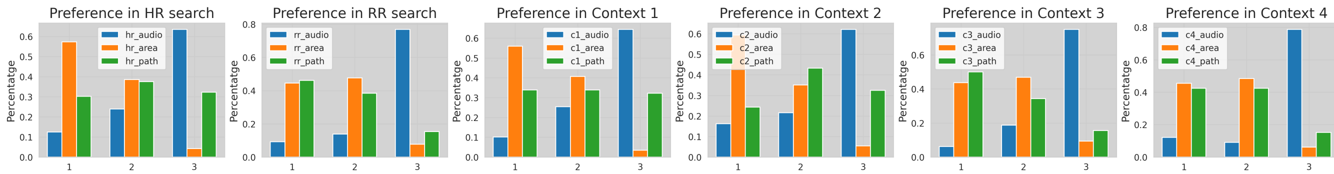

Figure 3: Preference ranking over plan representation

hr	Audio		Area		Path	
Audio	Tukey	Dunn	0.000	$3.33e^{-18}$	$6.29e^{-6}$	$1.01e^{-4}$
	Conover	Nemenyi	$6.90e^{-21}$	$1.24e^{-17}$	$6.33e^{-6}$	$1.84e^{-4}$
Area	0.000	$3.33e^{-18}$	Tukey	Dunn	$3.10e^{-7}$	$8.76e^{-6}$
	$6.90e^{-21}$	$1.24e^{-17}$	Conover	Nemenyi	$3.11e^{-7}$	$1.78e^{-5}$
Path	$6.29e^{-6}$	$1.01e^{-4}$	$3.10e^{-7}$	$8.76e^{-6}$	Tukey	Dunn
	$6.33e^{-6}$	$1.84e^{-4}$	$3.11e^{-7}$	$1.78e^{-5}$	Conover	Nemenyi

rr	Audio		Area		Path	
Audio	Tukey	Dunn	$1.74e^{-14}$	$9.61e^{-13}$	$4.15e^{-14}$	$2.11e^{-11}$
	Conover	Nemenyi	$8.94e^{-16}$	$2.98e^{-12}$	$2.49e^{-14}$	$6.16e^{-11}$
Area	$1.74e^{-14}$	$9.61e^{-13}$	Tukey	Dunn	0.858	1.000
	$8.94e^{-16}$	$2.98e^{-12}$	Conover	Nemenyi	1.000	0.912
Path	$4.15e^{-14}$	$2.11e^{-11}$	0.858	1.000	Tukey	Dunn
	$2.49e^{-14}$	$6.16e^{-11}$	1.000	0.912	Conover	Nemenyi

Figure 4: P-Value of the post-hoc tests applied to the plan representation ranking preference for hr (left) and rr (right) settings.

Factor Loadings	eigen values	Plan Reason. Audio	Plan Clear Audio	Plan Fair Audio	Plan Efficient Audio	Plan Logic Audio	Plan Inform. Audio	Plan Intuitive Audio	Robot Intellig. Audio	Robot Control. Audio	Robot Leader Audio	Robot Collab. Audio
factor 1	9.069	−0.050	−0.023	−0.044	0.037	−0.083	0.092	−0.045	0.205	0.034	0.188	0.034
factor 2	5.152	0.876	0.554	0.739	0.822	0.837	0.479	0.706	0.641	0.042	0.278	0.545
factor 3	3.578	0.100	−0.017	0.187	0.092	0.101	−0.030	−0.049	0.065	−0.081	−0.017	0.118
factor 4	2.148	0.063	0.323	−0.051	−0.080	0.068	0.202	0.346	0.224	0.026	0.109	0.216
factor 5	1.666	−0.001	0.160	−0.075	0.014	0.036	0.205	0.105	0.169	0.099	0.620	−0.007
factor 6	1.367	0.014	0.060	0.051	0.012	0.063	0.071	−0.086	−0.039	0.223	−0.140	−0.069
factor 7	1.116	0.109	0.271	−0.070	−0.013	0.072	0.458	−0.154	−0.223	0.084	0.155	0.066
factor 8	1.029	0.038	0.032	−0.071	0.059	−0.125	0.144	0.019	0.308	0.828	0.259	0.037
factor 9	0.956	−0.076	−0.028	0.048	0.040	−0.053	0.127	0.061	0.118	−0.007	0.051	0.123
factor 10	0.726	0.058	−0.178	0.168	−0.034	0.075	−0.070	−0.219	0.129	0.011	0.003	0.460

Factor Loadings	Plan Reason. Area	Plan Clear Area	Plan Fair Area	Plan Efficient Area	Plan Logic Area	Plan Inform. Area	Plan Intuitive Area	Robot Intellig. Area	Robot Control. Area	Robot Leader Area	Robot Collab. Area
factor 1	0.110	0.203	0.044	0.058	0.192	0.154	0.256	0.379	0.159	0.163	0.008
factor 2	0.073	0.153	0.010	0.157	0.120	0.231	0.114	−0.009	−0.075	0.030	0.152
factor 3	0.918	0.262	0.863	0.837	0.917	0.244	0.541	0.507	−0.072	0.290	0.548
factor 4	0.094	0.758	0.081	0.044	0.119	0.779	0.458	0.153	−0.033	0.084	0.303
factor 5	0.095	0.095	−0.030	0.062	0.024	0.021	0.107	0.250	0.502	0.825	0.055
factor 6	0.094	0.087	0.067	−0.028	−0.024	0.114	−0.010	0.283	0.501	0.150	0.043
factor 7	0.050	0.058	−0.002	−0.014	−0.047	0.128	−0.024	−0.363	−0.245	0.069	0.011
factor 8	−0.043	0.034	−0.084	−0.004	$-5.66e^{-4}$	$9.87e^{-4}$	0.071	0.044	0.302	−0.081	0.018
factor 9	−0.075	−0.044	0.107	0.058	0.015	0.054	0.217	−0.084	−0.027	0.171	−0.020
factor 10	−0.064	0.042	0.005	0.073	−0.032	0.089	0.132	0.306	−0.030	0.028	0.396

Factor Loadings	Plan Reason. Path	Plan Clear Path	Plan Fair Path	Plan Efficient Path	Plan Logic Path	Plan Inform. Path	Plan Intuitive Path	Robot Intellig. Path	Robot Control. Path	Robot Leader Path	Robot Collab. Path
factor 1	0.897	0.590	0.795	0.888	0.913	0.527	0.824	0.577	0.036	0.350	0.558
factor 2	−0.099	0.038	−0.019	−0.046	0.061	−0.067	−0.020	0.149	0.080	0.083	0.058
factor 3	0.087	0.073	0.019	0.158	0.106	−0.051	0.049	0.141	0.128	0.174	0.283
factor 4	0.022	0.169	0.135	−0.025	$-4.06e^{-4}$	0.241	0.072	0.237	0.158	0.048	0.330
factor 5	0.121	0.176	−0.063	0.086	0.018	0.119	0.206	0.070	0.013	0.343	0.002
factor 6	0.117	−0.014	−0.013	0.014	−0.020	0.155	0.015	0.234	0.806	0.352	−0.057
factor 7	−0.038	0.367	−0.083	0.058	0.088	0.549	0.089	−0.277	0.117	0.077	−0.013
factor 8	−0.015	0.261	0.042	−0.025	0.029	0.084	−0.012	−0.010	0.177	−0.003	0.081
factor 9	−0.086	0.185	0.077	0.018	0.004	−0.032	0.075	0.227	0.168	0.757	0.181
factor 10	−0.076	0.151	−0.027	−0.036	−0.003	0.149	0.009	0.206	−0.004	0.050	0.251

Figure 5: EFA factor loadings for the hr settings (coloring thresholds = {0.25,0.5,0.75})

The other four graphs in Figure 3 present rank preference data over each context. All four reach the same conclusion than their corresponding team configurations. That being said, a couple observable tendencies are worth mentioning. First, area over path preference seems to be more pronounced in context 2 (robot asking human) than in context 1 (human asking robot). Second, context 3 seems to present some tendency towards path preference over area, whilst in context 4 there is no visible difference.

5.2 Factors

We studied the plan and robot subjective perceptions of the participants through an Exploratory Factor Analysis (EFA). This study revealed many of the questions where explainable by the same factor and, thus, virtually asking for the same abstraction in the participants' judgement. As an example, the factor analysis of all the collected data in the hr setting is displayed in Figure 5.

In all settings and contexts we can identify three factors related to each representation format, which we labelled *"plan" subjective value* (factors 1, 2 and 3 in Figure 5). For each representation, the clarity of the plan is completely or partially characterised by another independent factor we labelled *"plan" clarity* (factors 4 and 8). Interestingly enough, participants valued clarity as an independent feature in the area plan, whilst there was a partial correlation with the subjective plan value in both audio and path representations. This may indicate less perceived value variability due to interface design. Also, there exists a partial correlation between the *clarity* perception of the audio and the area representations.

Other interesting factors are the factors we labelled *leadership* (5 and 9) and *controlling* (6 and 7). Some representations seem to maintain a higher correlation between these two features than others. Moreover, both properties correlate between representations, so some participants were more prone to generally consider the robot having these qualities than others. A similar proclivity, albeit with less impact, seems to exist concerning the perception of the *collaborative* factor (10).

6 CONCLUSIONS

The clearer conclusion of this study is that, when actively participating in a search task with a human-robot team, humans prefer to receive an assignation plan over a navigation plan proposal if confronted with a visual representation. Upon inspection of *leadership* and *controlling* factor loadings, one may hypotesise that preference stems from the excess of action restriction in navigation plans. Whether that is the actual cause and/or such phenomena repeats in other mediums should be studied in more detail. Similarly, while no clear preference between the path and area representations is provable in rr settings, the tendency observable in context 3 asks for a deeper study of the property perception in avatar or human as manager settings.

We remain cautious over the demonstrated preference of the visual representations over the audio proposal. Preference over such proposal may present a high variance due to wording or style. Also, some participants expressed difficulty in understanding spatial and demonstrative language in the proposed setting.

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