

Design and Evaluation of Service Robot's Proactivity in Decision-Making Support Process

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Service Robot – Support Human Decision-Making

Role examples

- Shop assistants (Canda et al., 2009)
- Receptionists (Lohse et al., 2014)

Previous work focuses on

• Question answering algorithm (Johannes et al., 2015)

Gap: manner of service

- Human proactivity (Grant et al., 2008)
- Affect worker's performance (Crant et al., 2000)



Source:

https://www.japantimes.co.jp/news/2014/12/01/business/tec h/softbanks-pepper-robot-debuts-coffee-machine-salesmanbic-camera/#.XMAfzej7SUk

Possible effects of robot's manner

- On users' perceptions (Sun et al., 2017)
- On users' behaviors (Takayama et al., 2009)

Anticipation-autonomy robot policy framework

- Principle: *high-, medium-, low*-proactivity
- Behavior policies in a decision-making support (DMS) process

Within-subject, Wizard-of-Oz experiment

- How people perceive and interact with robots of different proactivity
- Insights into designing robot's way of behaving

Definition: (derived from Grant et al., 2008)

Anticipatory action that robots initiate to impact themselves and/or others

- Anticipation Assumption on human's next action
- Initiation of action System **autonomy** (Sheridan et al., 1978)



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A Structured DMS Process



High-proactivity Robot Behavior Policy

- Strong assumptions, actively offer help
- *High* autonomy





Medium-proactivity Robot Behavior Policy

- Some assumptions, let user verify them
- *Medium* autonomy





Low-proactivity Robot Behavior Policy

- No assumptions, need user to tell what they want
- Low autonomy





Experiment to Evaluate the Effects

Settings

- Shoe shopping
- Robot assistant
- Laptop for browsing online category

Hypotheses

- Appropriateness
- Helpfulness

Behavior Analysis

- Turn-taking behaviors
- Purpose of users' turn
- Attitudes to recommended item



Three conditions

• *High-, medium-, low-*proactivity

Tasks

- Buy a pair of suitable shoes for a persona
- Reason needed
- Counterbalanced

Participants

- 36 (avg. age: 23.75)
- Gender-balanced
- ~ 40 mins / person

Persona	Shoe type	Color	Occasion	
Men	Oxfords	Black or Brown	Dress or Ca	sual
Women	Heels	Black or Beige	Dress or Ca	sual
Teens	Sneakers	Black or White	Skate or Ru	nning
Friendly Clever	Motivations		Personality	
Go-Getter	Fear		Introvert	Extrovert
Age: 32 Work: Software Developer Family: Single Location: San Jose, CA Character: The Computer N	Power Social		Loyal	Fickle
	Goals To cut down on unhe To measure multiple a To set goals and see 	althy eating and drinking habits aspects of life more scientifically and make positive impacts on his life	Preferred Channels Social Media Mobile	5
- 20	Frustrations Unfamiliar with weara Saturated tracking ma Manual tracking is too	ble technology rket time consuming	Email Traditional Ads	
"I feel like there's a smarter w me to transition into a heal lifestyle."	Bio Clark is a systems softw past couple years, has b of his health and perform	are developer, a "data junkie" and for the been very interested in tracking aspects nance. Clark wants to track his mood,	Brands	

Experiment Details

Wizard-of-Oz

- Infer intentions
- Trigger robot responses
- Button-based interface

Data Collection

- Questionnaires
- Post-study interview
- Video recording

SETTING				PROCESS		
Proactivity Task	highmen	medium women	low teens	direct help	greet need help?	respond
PREFERENCE					wait	
Color Occasion Merely index	blackdress	brown casual	<u>(52</u>)	direct reco	which color which occas reco	which index reco
HISTORY	ļ	1 - 15 - 8 -	<u>(53)</u>	direct justify features	need justify?	good words
EVENT HANDLE			<u>S4</u>	sense positive sense negative	like or not? positive	positive negative
no knowledge	Not sure	No info			negative	
simple answer	Of course	Sure	Yes			
transition	Ok, I see	Just a second			thanks, end	

Robot's Script Samples for Justification

- Modified from shoppers' reviews
- Test all the scripts in a pilot study







Figure 4: Means and standard errors of the user perception of the robots in terms of appropriateness (left) and helpfulness (right) on a 7-point Likert scale (+ : .05 , * : <math>p < .05, ** : p < .01).

- Least appropriate, though it can provide rich information
 Medium-proactivity robot
- Most helpful, more desirable to be served by it in the future *Low-proactivity robot*
- More user control, less interruptive



Figure 4: Means and standard errors of the user perception of the robots in terms of appropriateness (left) and helpfulness (right) on a 7-point Likert scale (+ : .05 , * : <math>p < .05, ** : p < .01).

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Results – on User Behaviors

Table: Average occurrences of users' behaviors during interaction

Theme	Turn-taking behaviors		
Category	Initating the turn	Competing for the turn	
Code example	(Robot is waiting) "I have a friend [] do you have any recommendation?"	(Robot is justifying the shoes) "No, I don't want this one"	
High	2.3 (2.02)	2.5 (2.09)	
Medium	3.0 (2.62)	2.0 (1.84)	
Low	6.2 (5.09)	0.7 (0.97)	

Adapt turn-taking behaviors to robots' manner

Results – on User Behaviors

Table: Average occurrences of users' behaviors during interaction

Theme	Purpose of users' turns		
Category	Making requests	Asking questions	
Code example	"Could you recommend me another pair?"	"Do you think it is suitable for a very busy woman?"	
High	2.5 (2.73)	0.8 (1.42)	
Medium	3.7 (3.09)	1.0 (2.16)	
Low	4.5 (3.65)	1.5 (2.22)	

More control over the conversation in *low* condition

Results – on User Behaviors

Table: Average occurrences of users' behaviors during interaction

Theme	Attitudes to recommended item		
Category	Positive	Negative	
Code example	(Robot gives recommendation) "Okay, I like this pair."	(During recommendation) "Give me another pair."	
High	2.2 (2.25)	1.8 (1.65)	
Medium	3.3 (2.35)	3.1 (3.08)	
Low	0.8 (1.02)	0.8 (0.95)	

Engage better in *medium* condition

Some Insights

Robot should maintain a mental model of human

- Things important for decisions: e.g., goal, preference, knowledge
- More considerate to verify the model before taking actions

Robot should express its capability

- For correct expectation
- Interactively help user obtain an correct metal model of robot, e.g., show uncertainty, explain the cause of communication failure, etc.

Robot behavior policy should be adaptive

- Context dependent, e.g., familiar with the items or not, in a hurry or not, etc.
- Sensitive to users' emotional reaction

Future Work

Test the generality of robot's proactivity design

- On diverse tasks
- In real-world settings
- With different user population

Consider different aspects of interaction dynamics

• E.g., action timing and robot's tones

Automate robot anticipation

- Multi-modality algorithm, e.g., gaze, face expression, gesture, head pose, etc.
- Decision-makers' mental model

Summary

Service robot in decision-making support (DMS) Define robot's proactivity in DMS settings

- Anticipation-autonomy policy framework
- *High-, medium-, low*-proactivity

Evaluations

- Perceptions: appropriateness and helpfulness
- User behaviors

Future design considerations for robot's manner

- Infer user's mental model
- Express its capability
- Adapt policy to context and user emotional reactions



Questions?



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