Modeling Conversational Flows for In-Store Mobile Decision Aids

Wi-Suk Kwon[1](✉), Veena Chattaraman[1], Kacee Ross[1], Kiana Alikhademi[2], and Juan E. Gilbert[2]

[1] Auburn University, Auburn, AL, USA
kwonwis@auburn.edu
[2] University of Florida, Gainesville, FL, USA

Abstract. Based on the Human-Elaboration-Object-Construal (HEOC) Contingency Model, we propose design principles for modeling conversational flows between consumers and an in-store mobile decision aid (MoDA) with artificial intelligence, functioning as a virtual sales associate. Through an on-going assessment of the quantity, type, and specificity of the decision preferences from the user's spoken input, MoDA is modeled to identify the user's levels of decision elaboration and construal, which leads to its recognition of the user's use of and shifts across four decision strategies commonly applied in consumer decision-making contexts. Upon identification of the user's decision-making strategy, MoDA is modeled to (1) identify strategy-relevant assistive tasks, (2) generate or access strategy- and task-relevant intelligence, and (3) utter strategy-, task-, and intelligence-relevant speech to naturally support the user's decision making strategy. The proposed design principles further map the types and examples of the agent tasks, intelligence, and speech required across the four consumer decision making strategies.

Keywords: Decision aid · Conversational flow · HEOC Contingency Model

1 Introduction

Consumer decision-making has changed with rapid technological advances including mobile technology. Physical retail stores have become merely one of many sources of product information for consumer decision making, along with a variety of online sources such as ecommerce sites, manufacturer sites, and online social media where user-generated product information (e.g., expert and customer reviews and ratings) is shared. With the abundance of information always available within a few clicks/taps, consumers no longer rush to make purchase decisions while they are in the store. The overload of product information makes it hard for consumers to acquire and process it fully within the store, motivating them to delay decisions until they have had the opportunity to review and compare choice alternatives online at a location and time of convenience to them. This trend naturally has led to the ever-increasing ecommerce

C. Stephanidis (Ed.): HCII Posters 2018, CCIS 852, pp. 302–308, 2018.
https://doi.org/10.1007/978-3-319-92285-0_42

sales [1]. In-store retailers are now compelled to offer consumers reasons to shop in the store instead of other channels, suggesting an acute need to reinvent their services to enhance customers' abilities to make decisions while in stores. In-store mobile decision aids (MoDA), which facilitate the acquisition and processing of product information and purchase decision making in the store while being able to physically examine the products, may address this need and provide in-store retailers with a competitive advantage over online retailers. In this paper, based on Chattaraman, Kwon, Eugene, and Gilbert's [2] Human-Elaboration-Object-Construal (HEOC) Contingency Model, we propose design principles for modeling conversational flows between a user and a language-based in-store MoDA which functions as a virtual sales associate and provides context-aware decision assistance in the way that caters to individual consumers' decision goals (e.g., product attributes or benefits sought) and constraints (e.g., time, product knowledge, cognitive resources).

2 Modeling In-Store MoDA Conversational Flows

The HEOC Contingency Model [3] postulates that an intelligent decision support system can predict a user's decision-making strategy based on the user's levels of decision elaboration (whether the user is likely to exert high or low effort in deliberating on the decision) and construal (whether the decision deliberation focuses on alternatives or attributes) identified from the user's decision preference input. Brand names and model names are examples of alternatives, whereas product features and functionality represent attributes. Specifically, the HEOC contingency model delineates the prediction of four common consumer decision-making strategies: lexicographic or LEX (low elaboration, attribute focus), satisficing or SAT (low elaboration, alternative focus), elimination by aspects or EBA (high elaboration, attribute focus), and weighted adding or WAD (high elaboration, alternative focus) [3]. Based on this model, we conceptualize a language-based in-store MoDA which

1. performs an on-going assessment and verification of the presence/absence, number, type, and specificity of the user's decision preference from his or her spoken input, with a goal of identifying the user's levels of decision elaboration (high vs. low) and construal (attribute vs. alternative focus),
2. predicts the user's adoption of and shifts across the four decision making strategies (i.e., LEX, SAT, EBA, WAD) based on the identified decision elaboration and construal levels,
3. identifies MoDA roles (e.g., decision preference prioritization aid, decision choice aid) and tasks that are relevant to the predicted decision-making strategy (see Table 1),
4. generates or accesses strategy- and task-relevant MoDA intelligence (see Table 1 for MoDA intelligence needed for each user strategy and task), and
5. utters strategy-, task-, and intelligence-relevant speech to naturally support the user's decision-making strategy (see Fig. 1 for the model and example of MoDA conversational flows for LEX decision makers).

Table 1. In-store mobile decision aids (MoDA) conversation flow design principles by user decision-making strategy: roles, tasks, and intelligence

MoDA role and tasks	MoDA intelligence	User decision-making strategy			
		LEX	SAT	EBA	WAD
Role 1: User Decision-Making Strategy Identifier (DMS_ID)					
1. Recognize alternatives voiced by user	• Ability to name alternatives (DMS_ID1)		✓		✓
2. Identify number of alternatives voiced by user	• DMS_ID1 • Ability to count alternatives (DMS_ID2)		✓		✓
3. Recognize attributes voiced by user	• Ability to name attributes (DMS_ID3)	✓	✓	✓	✓
4. Identify number of attributes voiced by user	• DMS_ID3 • Ability to count attributes (DMS_ID4)	✓	✓	✓	✓
5. Determine user's decision-making strategy	• DMS_ID2 • DMS_ID4 • Algorithm to determine user's decision elaboration level based on recognized alternatives and attributes voiced by user (DMS_ID5)	✓	✓	✓	✓
Role 2: Decision Preference Prioritization Aid (DPP_A)					
1. Inquire relative importance of attributes to user	• DMS_ID3 • Ability to process user language indicating level of importance (DPP_A1)			✓	
2. Recommend important attributes	• DMS_ID3 • Ability to prioritize attributes by widely-accepted degrees of importance (DPP_A2)	✓	✓		
3. Describe attributes to user	• DMS_ID3 • DPP_A2 • Knowledge of technical and practical meanings of each attribute and its levels (DPP_A3)	✓	✓	✓	✓
4. Inquire choice criteria per attribute	• DMS_ID3 • Knowledge of possible levels for each attribute (DPP_A4a) • Knowledge of attribute levels by alternative (DPP_A4b) • Ability to process user language that describes choice criteria (e.g., ranges, degrees, presence/absence) by attribute (DPP_A4c)		✓	✓	

(*continued*)

Table 1. (*continued*)

MoDA role and tasks	MoDA intelligence	User decision-making strategy			
		LEX	SAT	EBA	WAD
5. Recommend choice criteria per attribute	• Knowledge of widely-accepted criteria for each attribute (DPP_A5)		✓		
Role 3: Decision Choice Aid (DC_A)					
1. Show an alternative with highest value on the most important attribute	• DMS_ID1 • DMS_ID3 • DPP_A4b • Algorithm for rank-ordering alternatives by attribute (DC_A1)	✓			
2. Show an alternative that satisfies widely-accepted criteria on all attributes of importance to user	• DMS_ID1 • DMS_ID3 • DPP_A4a • DPP_A4b • DPP_A5		✓		
3. Help user with successive reduction of consideration set by applying attributes and their criteria in order of importance	• DMS_ID1 • DMS_ID3 • DPP_A1 • DPP_A4b			✓	
4. Show an alternative that meets user's choice criteria on all attributes voiced by user	• DMS_ID1 • DMS_ID3 • DPP_A4b • DPP_A4c		✓	✓	
5. Show a potential consideration set of alternatives and their attribute levels for user deliberation of trade-offs	• MS_ID3 • DPP_A4b • Algorithm for forming a consideration set (e.g., top alternatives on each attribute voiced by user, alternatives with top average ranks/ratings on all attributes voiced by user) (DC_A5a) • Ability to visualize the trade-offs (DC_A5b)				✓

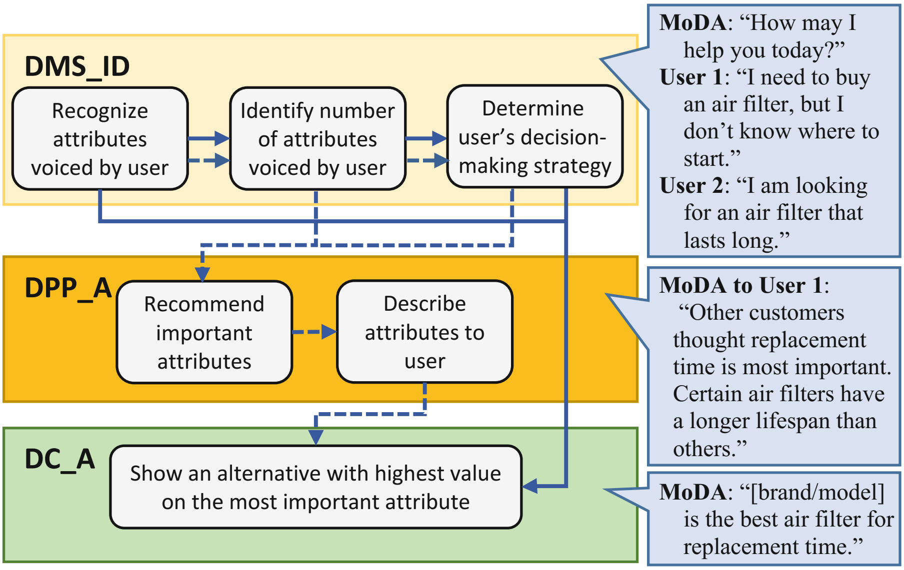

Fig. 1. Model and example of MoDA conversational flows for LEX decision makers. Note: dashed arrows are flows for User 1, and solid arrows are for User 2.

For example, through a conversation with a user, MoDA may find that the user is lacking product domain knowledge and unable to articulate decision preferences (see User 1 in Fig. 1), in which case MoDA initially predicts the user as a low elaborator who could be helped by learning about product attributes (i.e., a LEX decision maker). With this prediction, MoDA would now play a role as a decision preference prioritization aid (DPP_A) by recommending an important attribute (see Fig. 1 and DPP_A Task #2 in Table 1) and describing this attribute to the user (see Fig. 1 and DPP_A Task #3 in Table 1), and then shifting to a role as a decision choice aid (DC_A) by proposing an alternative that performs best on the recommended attribute (see Fig. 1 and DC_A Task #1 in Table 1). On the other hand, if the conversation with the user reveals that the user has a clearly preferred product attribute (see User 2 in Fig. 1), although MoDA may still classify this user as a LEX decision maker, it can skip the DPP_A role and directly engage in a DC_A role by proposing the best-performing alternative on the user-voiced attribute. In other scenarios (e.g., when user input reveals his or her preference for certain alternatives such as brands or models [i.e., SAT or WAD] and/or indicates the user's knowledge or motivation to process elaborately many types of attributes [i.e., EBA or WAD]), their respective roles, tasks, and types of intelligence implemented by MoDA will vary as outlined in Table 1.

3 Conclusion

Most intelligent agents in consumer environments such as ecommerce sites have served merely as navigational/procedural aids (e.g., Alaska Airlines' *Jen*). Previous literature on recommendation agents has assumed that users have well-defined decision preferences [4, 5], and hence has lacked in developing the aids for preference formation and prioritization. Previous work has also assumed that users are able and motivated to engage in an elaborative and rational decision-making strategy for an "accurate" decision [6–9]. However, consumer decision making tends to be constructive (i.e., consumers may form preferences as they learn about options) and is characterized by shifts across multiple decision-making strategies. Further, decision aid literature is scant on decision aids for the spoken language-based interface, which is the most natural mode of interaction between human agents and consumers in stores (cf., [10, 11]). The in-store MoDA conversational flow design principles proposed in this paper, based on the HEOC Contingency Model, articulate the specific roles, tasks, and types of intelligence (ability and knowledge) to be implemented in designing language-based intelligent agents that understand the consumer's use of and shifts across four common decision-making strategies during an in-store shopping process. The proposed approach contributes to advancing the intelligent agent literature by enlightening the *user intent* aspect of natural language understanding (NLU), which is a key area for current and future artificial intelligence research.

Acknowledgements. This material is based in part upon work supported by the National Science Foundation under Grant Numbers IIS-1527182 and IIS-1527302. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

References

1. Digital Commerce 360: Internet Retailer. U.S. e-commerce sales grow 16.0% in 2017, https://www.digitalcommerce360.com/article/us-ecommerce-sales/. Accessed 16 Mar 2018
2. Chattaraman, V., Kwon, W.-S., Eugene, W., Gilbert, J.: Developing and validating a naturalistic decision model for intelligent language-based decision aids. Hum. Fact. Ergon. Soc. Annu. Meet. **61**(1), 176–177 (2017)
3. Bettman, J.R., Luce, M.F., Payne, J.W.: Constructive consumer choice processes. J. Consum. Res. **25**(3), 187–217 (1998)
4. Chen, H., Lam, P.P., Chan, H.C., Dillon, T.S., Cao, J., Lee, R.S.: Business-to-consumer mobile agent-based internet commerce system (MAGICS). IEEE Trans. Syst. Man Cybern. Part C Appl. Rev. **37**(6), 1174–1189 (2007)
5. Xiao, B., Benbasat, I.: E-commerce product recommendation agents: use, characteristics, and impact. MIS Q. **31**(1), 137–209 (2007)
6. Lee, Y.E., Benbasat, I.: Interaction design for mobile product recommendation agents: supporting users' decisions in retail stores. ACM Trans. Comput. Hum. Interact. **17**(4), 17 (2010)
7. Swaminathan, V.: The impact of recommendation agents on consumer evaluation and choice: the moderating role of category risk, product complexity, and consumer knowledge. J. Consum. Psychol. **13**(1–2), 93–101 (2003)

8. Häubl, G., Trifts, V.: Consumer decision making in online shopping environments: the effects of interactive decision aids. Mark. Sci. **19**(1), 4–21 (2000)
9. Fleming, M., Cohen, R.: A decision procedure for autonomous agents to reason about interaction with humans. In: AAAI 2004 Spring Symposium on Interaction between Humans and Autonomous Systems over Extended Operation, pp. 81–86. (2004), http://www.aaai.org/Papers/Symposia/Spring/2004/SS-04-03/SS04-03-016.pdf. Accessed 16 Mar 2018
10. Maass, W., Kowatsch, T., Janzen, S., Varshney, U.: A natural language technology-enhanced mobile sales assistant for in-store shopping situations. In: Tuunainen, V., Nandhakumar, J., Rossi, M., Soliman, W. (eds.) 19th European Conference on Information Systems (ECIS), vol. 142. Helsinki, Finland (2011), https://www.alexandria.unisg.ch/72472/1/Maass%20et%20al%202011%20NLT-MSA.pdf. Accessed 16 Mar 2018
11. Kowatsch, T., Maass, W.: In-store consumer behavior: how mobile recommendation agents influence usage intentions, product purchases, and store preferences. Comput. Hum. Behav. **26**(4), 697–704 (2010)