Don't Take it Personally: Resistance to Individually Targeted Recommendations from Conversational Recommender Agents

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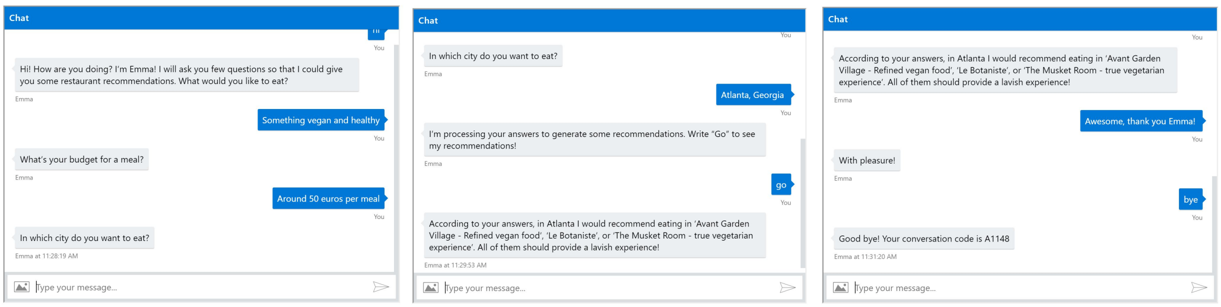

Figure 1: Conversational recommender agent providing user-initiated recommendations condition.

ABSTRACT

Conversational recommender agents are artificially intelligent recommender systems that provide users with individually-tailored recommendations by targeting individual needs and communicating in a flowing dialogue. These are widely available online, communicating with users while demonstrating human-like (anthropomorphic) social cues. Nevertheless, little is known about the effect of their anthropomorphic cues on users' resistance to the system and recommendations. Accordingly, this study examined the extent to which conversational recommender agents' anthropomorphic cues and the type of recommendations provided (user-initiated and system-initiated) influenced users' perceptions of control, trustworthiness, and the risk of using the platform. The study assessed how these perceptions, in turn, influence users' adherence to the recommendations. An online experiment was conducted among users with conversational recommender agents and web recommender platforms that provided user-initiated or system-initiated restaurant recommendations. The results entail that user-initiated recommendations, compared to system-initiated, are less likely to affect users' resistance to the system and are more likely to affect their adherence to the recommendations provided. Furthermore, the study's findings suggest that these effects are amplified for conversational recommender agents, demonstrating anthropomorphic cues, in contrast to traditional systems as web recommender platforms.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; **User studies**; **HCI theory, concepts and models**; • **Security and privacy** → *Usability in security and privacy*; • **Information systems** → *Decision support systems*; **Presentation of retrieval results**; **Personalization**; **Search interfaces**; • **Applied computing** → **Psychology**; **Marketing**; *Online shopping*.

KEYWORDS

Recommender Systems, Conversational Agents, Personalization, Chatbots, E-commerce, Anthropomorphism, Privacy, Trust

ACM Reference Format:
Guy Laban and Theo Araujo. 2022. Don't Take it Personally: Resistance to Individually Targeted Recommendations from Conversational Recommender Agents. In *Proceedings of the 10th International Conference on Human-Agent Interaction (HAI '22), December 5–8, 2022, Christchurch, New Zealand.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3527188.3561929

1 INTRODUCTION

Recommender systems, computer software that provides users with suggestions for supporting decision-making processes [69], often use one-to-one marketing techniques [4, 62, 73]. These marketing procedures aim to target and tailor suggestions for individuals [72]. As these have become more common online, artificial entities such as conversational agents, artificially intelligent computer programs that interact with users by using natural language [33, 74], are being integrated as conversational recommender agents [19, 20, 68]. These are already applied by marketers to provide consumers with individually tailored experiences; this is done by targeting individual needs and communicating in a flowing dialogue, potentially increasing consumer engagement (see [33]). Designed with cognitive architectures to communicate in a human-like way [42, 58], these conversational agents are often described and perceived as anthropomorphic and are evaluated in a human-like way [2, 11]. While conversational recommender agents are embraced in the industry [33], it is still unclear how users perceive these, how their anthropomorphic cues influence these perceptions and the corresponding recommendations.

Individually tailored recommendations are often either user-initiated (customized) or system-initiated (personalized). User-initiated recommendations depend on users proactively disclosing relevant information. Alternatively, system-initiated recommendations are based on previously collected consumer data such as online behavior and personal information [5, 15, 41, 45, 75–77]. As such, these techniques often require users to either proactively or reactively disclose private information [76, 84]. The act of self-disclosure, being a key factor for building relationships [44, 61], can facilitate relationships and improve bonding. Nonetheless, when the disclosure is forced it can feel invasive, unnatural, uncomfortable, or unethical [1, 23]. Accordingly, tailored marketing can have positive persuasive implications [72], but the necessity of disclosing information [17, 46] can also trigger resistance among users (e.g., [6, 79]).

The persuasive implications of anthropomorphic agents in marketing settings are widely addressed in the literature (e.g., [15, 22, 36, 41, 53, 60]), yet, there is a knowledge gap regarding the consequences of anthropomorphic conversational recommender agents. Previous studies show that based on different visual (i.e., design) and social cues people evaluate artificial agents more positively (e.g., [49]), are willing to take advice from artificial agents (e.g., [63]), and disclose personal information to these over time (e.g., [52]). While previous studies show that people are may not differ in their disclosure levels towards artificial agents based on their anthropomorphic cues of embodiment [50, 51], it is unclear if anthropomorphic embodiment will affect people's perceptions in e-commerce settings, and when disclosure is reactive or proactive. Considering the persuasive implications of recommender systems and one-to-one marketing techniques [17, 46, 72], there is a need to further explore how conversational recommender agents' anthropomorphic cues may influence this process. The potential contribution of anthropomorphic cues to the recommender system experience should therefore be further explored to understand how these affect users' resistance to the system and the recommendations provided.

Through an online experimental design with conversational recommender agents and web recommender platforms that provided user-initiated or system-initiated restaurant recommendations, two main aims were addressed. First, this study aimed to reduce the knowledge gap regarding the implications of recommender systems' anthropomorphic cues on user resistance to both the system and the recommendation provided. Moreover, the study aimed to expand the theoretical scope of proactive and reactive information disclosure in online marketing settings and to evaluate the influences anthropomorphic cues have on these procedures. Hence, the following research question is proposed:

RQ: To what extent do conversational recommender agents' anthropomorphic cues and the type of recommendations provided affect online users' adherence to recommendations?

2 METHODS

2.1 Design and Procedure

A two (anthropomorphic cues: conversational recommender agent vs. web recommender platform) by two (type of recommendations: user-initiated vs. system-initiated) between-subjects factors online experiment was conducted. Participants were informed regarding their rights and were asked to provide their informed consent; participants who consented then began the experiment. First, participants answered a set of demographic questions and an attention check. Then, they were randomly assigned to one of the four groups and received corresponding instructions. Using either a conversational recommender agent or a web recommender platform, participants answered three open-ended questions—disclosing a favourite cuisine, their budget for a meal, and a preferable location for a restaurant. Accordingly, the recommender system provided either user-initiated or system-initiated recommendations. When receiving user-initiated recommendations, the platform explained that the recommendations were based on the participant's answers, whereas when receiving system-initiated recommendations, the platform explained that the recommendations were based on the participant's online behaviour and social media information. Participants were informed that the manipulation should not take more than three minutes. After completing the task, participants evaluated the platform, and the recommendations, and self-reported their affinity with technology and need for cognition. Once participants completed the experiment, they were debriefed about the study and provided with the researcher's contact information. The study received an ethics review board approval.

2.2 Participants

A priori sample size computation using the software G*Power version 3.1 [31, 32] indicated that for finding a medium effect size (R^2 = 0.09) with 95% confidence intervals, the required sample size is at least 180 units. A total of 300 participants were recruited using Amazon Mechanical Turk (MTurk). The sample consisted of English-speaking people between the ages of 19 to 65, who reside in the US, and reported using a mobile or desktop instant messaging application. Out of 300 participants, 13 were dropped because of technical issues and another six for failing the attention checks. An outliers check was conducted using values of Mahalanobis distance, Cook's D, and Leverage, controlling for participant's manipulations' perceived realism. Units that were considered outliers by at least two of the distance or leverage values were individually examined, resulting in 15 dropped cases. Thus, the final sample size consisted of 266 total participants between the ages of 19 to 65 (M = 38.33, SD = 12.20), with 42.1% females, and most have completed a bachelor's degree (51.5%) or secondary school/high school (32.7%).

2.3 Stimuli

2.3.1 Anthropomorphic cues. The independent variable "anthropomorphic cues" concerned the systems' demonstration of human-like communication through the manipulation of language, dialogue,

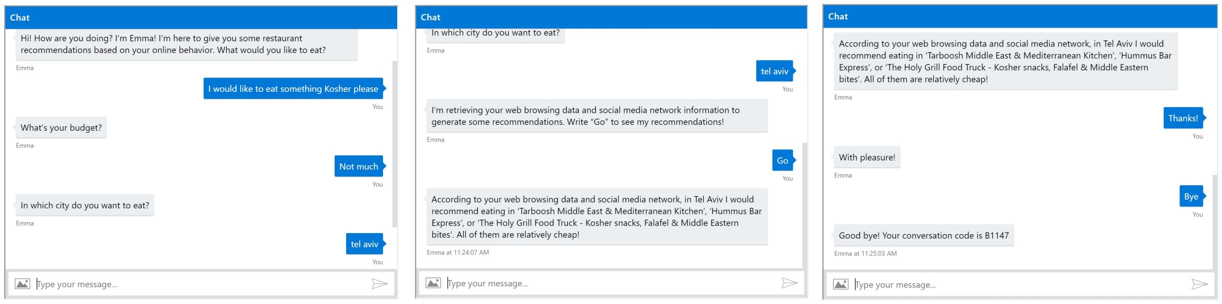

Figure 2: Conversational recommender agent providing system-initiated recommendations condition.

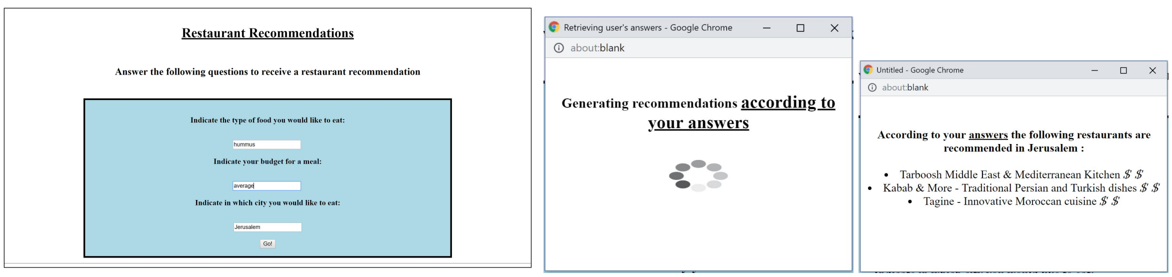

Figure 3: Web platform providing user-initiated recommendations condition.

symbols, and icons [20, 21]. For this study, anthropomorphic cues of the conversational recommender agent were manipulated by employing an artificial conversational agent (a chatbot) with a human name ("Emma") that spoke using first-person singular pronouns. Emma communicated with the participants via online chat and described recommendations with nouns and adjectives (e.g., "These restaurants should provide a lavish experience!" when describing expensive restaurants). Emma also used greetings (e.g., "Hi") and reacted to users' statements (e.g., "My pleasure!") (see Figures 1 and 2). The agents were created using the Conversational Agent Research Toolkit [3]. A recommender system that lacked anthropomorphic cues was manipulated by using a traditional recommender system (i.e., a web recommender platform). The platform utilized buttons, icons, and windows (e.g., a "Go" button to submit values and a pop-up window to show recommendations), to stimulate the impression of a standard website [77]. Recommendations were described with a passive voice and common symbols and icons (e.g., "$" for describing budget) (see Figures 3 and 4).

2.3.2 Type of Recommendations. The independent variable "type of recommendation" is concerned with the tailoring technique employed to generate a recommendation. The concept includes two types of recommendations following Sundar's and Marathe's definitions [77]—customized and personalized, whereas here we define these as user-initiated and system-initiated. User-initiated (customized) recommendations are the result of the user's conscious proactive information disclosure. System-initiated (personalized) recommendations are based on the user's reactive disclosure of online behaviour and social media information. While participants in both conditions went through the same procedure, they were explicitly informed that the recommendations they received were either based on their answers (i.e., user-initiated; see Figures 1 and 3) or on their online behaviour and social media information (i.e., system-initiated; see Figures 2 and 4).

2.4 Measurements

Principal axis factoring (PAF) analysis was conducted with 51 items that measure the concepts 'perceived anthropomorphism' (5 items), 'perceived control' (6 items), 'trustworthiness' (6 items), 'perceived risk' (8 items), 'affinity with technology' (9 items) and 'need for cognition' (17 items). After inspecting the correlation matrix, it is noticeable that there is no threat of multicollinearity and that there are no threats to the variables' discriminant validity, as none of the correlations is above .85 (the highest correlation is .71). Moreover, the Kaiser-Meyer-Olkin measure of sampling adequacy was .89, above the recommended value of .6, and Bartlett's test of sphericity was significant, $\chi^2(1275) = 10077.18$, $p < .001$. The diagonals of the anti-image correlation matrix were all over .5, supporting the inclusion of each item in the analysis. Eight components were found with an eigenvalue above 1 according to the eigenvalue criterion. Together, these components explain 68.23% of the variance in the original items. According to the results of an oblique rotation, the items were divided between the components, which can be labelled as (1) 'need for cognition (looking for cognition)', (2) 'perceived risk', (3) 'perceived anthropomorphism', (4) 'locus of causality', (5) 'internal controllability', (6) 'need for cognition (avoiding cognition)', (7) 'affinity for technology', and (8) 'trustworthiness'.

2.4.1 Manipulation checks.

Perceived anthropomorphism. The anthropomorphic cues manipulation was assessed using an adapted scale from [9, 65]. This consisted of five items evaluated on a seven-point semantic bipolar scale. These items represent the possible identification differences between a human and a machine, where a higher score indicates humanlike agent behaviour, and a lower score represents a mechanical behaviour that is associated with robots and machines [9]. The scale was reliable (α = .94, M = 4.12) and a mean index was created accordingly.

Attribution of the recommendations to a source. The type of recommendations manipulation was assessed using a manifest dichotomous item. This asked participants to attribute the recommendations they received to either their own answers or their online behaviour and social media information.

2.4.2 Mediators.

Perceived control. Perceived control refers to one's internal attribution of control during the procedure. The concept was measured using the locus of causality and internal controllability indicators from the Causal Dimension Scale [70], based on Weiner's model of attribution [82]. Both scales include three bipolar items with semantic differences on a seven-point range that were adjusted to fit the context of the current study and experimental treatment, rather than to general events. The scale was reliable (α=.82, M=3.86) and a mean index was created accordingly.

Trustworthiness. Trustworthiness refers to the extent of the participant's self-assessed state of trust in the platform after exposure to the treatment [16]. Following [16], trustworthiness in the context of information systems includes two indicators, general trust in the platform and trust regarding privacy [64]. General trust in the platform was measured using three Likert-scale statements on a seven-point range, adapted from [83]. Trust regarding privacy was measured using three more Likert-scale statements, also on a seven-point range, adapted from [25]. The items were adjusted to fit the context of the current study and referred to the experimental treatment rather than general events. The scale was reliable (α = .91, M = 4.52) and a mean index was created accordingly.

Perceived risk. When a situation or a process creates a sense of concern, discomfort, and/or anxiety, this is known as perceived risk [26]. Following [16], perceived risk in the context of information systems includes two indicators, general risk and privacy concerns. General risk was measured using four Likert-scale statements on a seven-point range adapted from [16, 24, 59]. Privacy concerns were measured using four Likert-scale statements on a seven-point range adapted from [16, 24, 25]. The items were adjusted to fit the context of the current study and referred to the experimental treatment rather than general events. The scale was reliable (α = .94, M = 3.79) and a mean index was created accordingly.

2.4.3 Dependent variable.

Adherence to recommendations. The concept addresses the participant's likelihood to follow or avoid the recommendations provided by the recommender system. As a manifest concept, participants were asked to rate their likelihood to follow or avoid the recommendations provided on a seven-point scale.

2.4.4 Control variables.

Table 1: Summary Statistics of the Variables

	Mean	SD	α	min	max
Perceived Anthropomorphism	4.12	1.73	0.94	1	7
Perceived Control	3.86	1.27	0.82	1	7
Trustworthiness	4.52	1.30	0.91	1	7
Perceived Risk	3.79	1.47	0.94	1	7
Adherence to Recommendations	4.94	1.73	-	1	7
Affinity with Technology	3.91	0.72	0.90	1	5
Need for Cognition	3.44	0.80	0.93	1	5
Age	38.33	12.20	-	19	65
Perceived Realism	5.01	1.79	-	1	7
N	266				

Affinity for technology. Affinity for technology controls for participant's familiarity and personal affection towards technology [28]. This concept was measured using nine items with five-point Likert-scales, adapted from [28]. The scale was reliable (α =.90, M = 3.91) and a mean index was created accordingly.

Need for cognition. Need for cognition refers to the degree to which an individual is willing to engage with and would enjoy a cohesive information processing task [12]. This concept was measured using 17 items with five-point Likert-scales, adapted from[12]. The scale was reliable (α = .93, M = 3.44) and a mean index was created accordingly.

Demographics. The questionnaire included the demographic items age, biological sex, country of residence, country of origin, and the highest level of completed education.

Manipulations' perceived realism. To control for the objectivity of the manipulation in the manipulation checks and outlier inspection, participants were asked to evaluate how realistic they found the manipulations to be, on a seven-point Likert-scale.

3 RESULTS

3.1 Pilot

To test the experiment's stimuli, a pilot was conducted with two (anthropomorphic cues: recommender agent vs. web recommender platform) by two (type of recommendations: customization vs. personalization) between-subjects factors online experiment. A total of 150 participants between the ages of 19 and 57 (M = 32, SD = 8.02) were recruited using MTurk, of which 46.3% were females, and most have completed a bachelor's degree (56.8%) or secondary school/high school (24.9%). Participants were randomly assigned to one of the four groups, and after completing the manipulation task, participants answered a questionnaire evaluating the platform's anthropomorphic cues and indicating the source of information upon which the recommendations were based. Independent-samples t-test indicated that conversational recommender agents (M = 4.71, SD = 1.56) were perceived as more anthropomorphic than web recommender platforms (M = 3.53, SD = 1.69), $t(148)$= -5.90, p < .001, 95%CI [1.57,-.78], d = .72. A chi-square test demonstrated that system-initiated recommendations are associated with participants' attributing the recommendations to their online behaviour, $\chi^2(1)$ = 75.12, φ = -.53, p < .001. Hence, both conditions were successfully

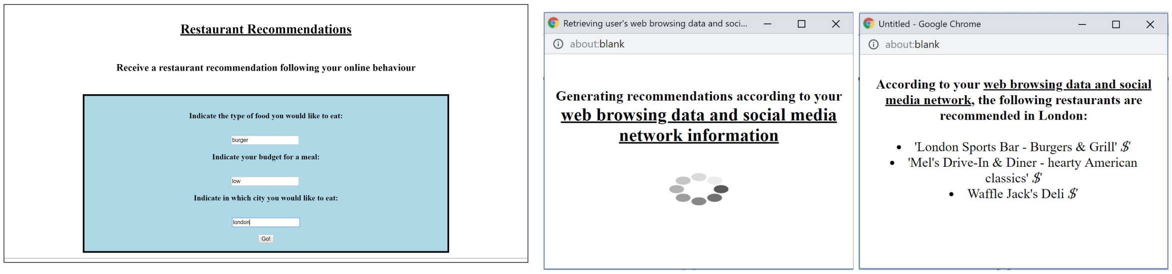

Figure 4: Web platform providing system-initiated recommendations condition.

manipulated in the pilot, and therefore the stimuli could be used in the main experiment.

3.2 Manipulation checks

A one-way ANCOVA indicated that conversational recommender agents (M = 4.51, SE = .11, 95%CI [4.29,4.73]) were perceived as more anthropomorphic than web recommender platforms (M = 3.73, SE = .11, 95%CI [3.51,3.95]), F(1,263) = 24.06, p < .001, controlling for the manipulations' perceived realism. A binary logistic regression indicated that participants are significantly less likely to attribute user-initiated recommendations, compared to system-initiated, to their online behaviour than to their answers, β = -2.75, p < .001, OR = .06, 95%CI [.03,.13], holding the manipulations' perceived realism constant. Therefore, both conditions were successfully manipulated.

3.3 Randomization

To test whether the sample data was distributed equally across conditions randomization checks were performed. A one-way ANOVA was performed for age, F(3, 265) = .20, p = .894. Chi-square tests were used to check both the level of education, $\chi^2(12)$ = 6.64, p = .880, and gender, $\chi^2(3)$ = 7.01, p = .072. It can therefore be concluded that there were no issues with the distribution of the sample data.

3.4 Analysis

A moderated mediation analysis was conducted using Model 8 of PROCESS Macro 3.2 to SPSS [39] to explain the outcome of adherence to recommendations based on the platforms' anthropomorphic cues and the type of recommendations as independent variables and moderators; perceived control, trustworthiness, and perceived risk as mediators; and age, gender, level of education, affiliation with technology, and need for cognition as covariates.

3.4.1 Perceived Control. The model explaining perceived control was significant, R = .30, F(8, 257) = 3.13, p = .002, with 8.9% (R^2= .089) of the variance in perceived control explained. The main effect of the platforms' anthropomorphic cues was significant, β = .49, t(257) = 2.29, p = .023. The main effect of the type of recommendations, however, was not. The unconditional interaction effect of the platforms' anthropomorphic cues and the type of recommendations was significant, β = -.62, t(257) = -2.01, ΔR^2 = .01, ΔF(1, 257) = 4.05, p = .045 (see table 2). A test for conditional effects revealed that conversational recommender agents had a significant positive effect on perceived control, for user-initiated recommendations, β = .49, t(257) = 2.29, p = .023, 95%CI [.07, .91], while the effect is insignificant for system-initiated recommendations. The test also found that user-initiated recommendations had a significant positive effect on perceived control for conversational recommender agents, β = -.67, t(257) = -3.09, p = .002, 95%CI [-1.09, -.24], while the effect is insignificant for web recommender platforms (see table 3).

3.4.2 Trustworthiness. The model explaining trustworthiness was significant, R = .27, F(8, 257) = 2.58, p = .010, with 7.4% (R^2 = .074) of the variance in trustworthiness explained. The main effect of the platforms' anthropomorphic cues was not significant. However, the main effect of the type of recommendation was significant, β = -.51, t(257) = -2.25, p = .025. The unconditional interaction effect of the platforms' anthropomorphic cues and the type of recommendation was not significant (see table 2). A test for conditional effects revealed that there were no significant effects of the platforms' anthropomorphic cues on trustworthiness for both user-initiated and system-initiated recommendations. The test did find, however, that user-initiated recommendations have a significant positive effect on trustworthiness for conversational recommender agents, β = -.53, t(257) = -2.40, p = .017, 95%CI [-.97, -.10], and web recommender platforms, β = -.51, t(257) = -2.25, p = .025, 95%CI [-.95, -.06] (see table 3).

3.4.3 Perceived Risk. The model explaining perceived risk was significant, R = .36, F(8, 257) = 4.75, p < .001, with 12.9% (R^2 = .129) of the variance in perceived risk explained. The main effect of the platforms' anthropomorphic cues was not significant. However, the main effect of the type of recommendations on perceived risk, was significant, β = .62, t(257) = 2.51, p = .013. The unconditional interaction effect of the platforms' anthropomorphic cues and the type of recommendation was not significant (see table 2). A test for conditional effects revealed no significant effects of the platforms' anthropomorphic cues on perceived risk for both user-initiated and system-initiated recommendations. The test did find, however, that system-initiated recommendations have a significant positive effect on perceived risk, for conversational recommender agents, β = 1.14, t(257) = 4.66, p < .001, 95%CI [.66, 1.62], and web recommender platforms, β = .62, t(257) = 2.51, p = .013, 95%CI [.13, 1.11] (see table 3).

3.4.4 Adherence to Recommendations. The overall model significantly explained users' adherence to recommendations, R = .61, F(11, 254) = 13.33, p < .001, with the model explaining 36.6% (R^2 = .366) of the variance in adherence to recommendations. When

Table 2: Unconditional effects

	Adherence to Recommendations	Perceived Control	Trustworthiness	Perceived Risk
Anthropomorphic cues	0.82**	0.49*	0.05	-0.25
	[0.33,1.31]	[0.07,0.91]	[-0.39,0.48]	[-0.73,0.23]
Types of recommendations	-0.03	-0.05	-0.51*	0.62*
	[-0.54,0.47]	[-0.48,0.39]	[-0.95,-0.06]	[0.13,1.11]
Interaction term	-0.73*	-0.62*	-0.02	0.51
	[-1.44,-0.03]	[-1.23,-0.01]	[-0.65,0.60]	[-0.17,1.20]
Perceived control	0.37***			
	[0.22,0.51]	-	-	-
Trustworthiness	0.64***			
	[0.47,0.82]	-	-	-
Perceived risk	-0.22**	-	-	-
	[-0.38,-0.05]			
Need for cognition	0.14	0.19	-0.06	-0.25*
	[-0.11,0.39]	[-0.03,0.40]	[-0.28,0.16]	[-0.49,-0.01]
Affinity for technology	0.08	-0.16	0.25*	0.07
	[-0.20,0.36]	[-0.40,0.07]	[0.00,0.49]	[-0.20,0.34]
Gender	0.32	0.29	0.11	-0.03
	[-0.04,0.67]	[-0.01,0.60]	[-0.21,0.43]	[-0.38,0.32]
Age	-0.01	0.01	-0.01	-0.00
	[-0.03,0.00]	[-0.00,0.02]	[-0.02,0.00]	[-0.02,0.01]
Level of education	-0.13	-0.18	0.03	0.26*
	[-0.38,0.11]	[-0.39,0.03]	[-0.19,0.25]	[0.02,0.50]
R^2	0.37	0.09	0.07	0.13
F	13.33	3.13	2.58	4.75
N	266	266	266	266

95% confidence intervals in brackets
* p <0.05, ** p <0.01, *** p <0.001
Notes: Interaction term - Anthropomorphic cues * Types of recommendations

Table 3: Conditional direct effects

		Perceived control		
		β	t	95% CI
Anthropomorphic cues	User-initiated	0.49* (0.21)	2.29	0.07, 0.91
	System-initiated	-0.13 (0.22)	-0.58	-0.56, 0.31
Type of recommendations	Recommender Agent	-0.67* (0.22)	-3.09	-1.09, -0.24
	Web Recommender Platform	-0.05 (0.22)	-0.21	-0.48, 0.39
		Trustworthiness		
		β	t	95% CI
Anthropomorphic cues	User-initiated	0.05 (0.22)	0.21	-0.39, 0.48
	System-initiated	0.02 (0.23)	0.10	-0.43, 0.47
Type of recommendations	Recommender Agent	-0.53* (0.22)	-2.40	-0.97, -0.10
	Web Recommender Platform	-0.51* (0.23)	-2.25	-0.95, -0.06
		Perceived risk		
		β	t	*95% CI*
Anthropomorphic cues	User-initiated	-0.25 (0.24)	-1.04	-0.73, 0.23
	System-initiated	0.26 (0.25)	1.05	-0.23, 0.75
Type of recommendations	Recommender Agent	1.14*** (0.24)	4.66	0.66, 1.62
	Web Recommender Platform	0.62* (0.25)	2.51	0.13, 1.11
		Adherence to Recommendations		
		β	t	95% CI
Anthropomorphic cues	user-initiated	0.82** (0.25)	3.32	0.34, 1.31
	System-initiated	0.09 (0.25)	0.36	-0.41, 0.59
Type of recommendations	Recommender Agent	-0.77** (0.26)	-2.95	-1.28, -0.26
	Web Recommender Platform	-0.03 (0.26)	-0.13	-0.54, 0.47

Standard errors in parentheses
* p <0.05, ** p <0.01, *** p <0.001

controlling for the anthropomorphic cues, types of recommendations, and their interaction term, all the mediators were found to have a significant direct effect on adherence to recommendations. These were perceived control, β = .37, $t(254)$ = 5.01, p < .001; trustworthiness, β = -.64, $t(254)$ = -7.18, p < .001; and perceived risk, β = -.22, $t(254)$ = -2.63, p = .009. The model revealed that when controlling for the mediators, the platforms' anthropomorphic cues had a significant main effect on adherence to recommendations, β = .82, $t(254)$ = 3.32, p = .001, while the type of recommendations did not. In addition, their interaction term had a significant unconditional direct effect on adherence to the recommendations, β = -.73, $t(254)$ = -2.05, ΔR^2 = .01, $\Delta F(1, 254)$ = 4.20, p = .042 (see table 2).

A test for conditional effects revealed that conversational recommender agents had a significant positive direct effect on adherence to the recommendations for user-initiated recommendations, β = .82, $t(254)$ = 3.32, p = .001, 95%CI [.34, 1.31], while the effect is insignificant for system-initiated recommendations. Additionally, user-initiated recommendations had a significant positive direct effect on adherence to recommendations for conversational recommender agents, β = -.77, $t(254)$ = -2.95, p = .004, 95%CI [-1.28, -.26], while the effect is insignificant for web recommender platforms (see table 3).

3.4.5 Indirect effects. To check for indirect effects and moderated mediation, 95% confidence intervals of 5000 bootstrapped samples

[66] test for moderated mediation (see [37, 38]) was conducted (see table 4).

Mediated by Perceived Control. The test revealed that conversational recommender agents had a significant positive indirect effect on adherence to recommendations through perceived control for user-initiated recommendations, β = .18, SE = .09, 95%CI [.29, .37], yet the effect was insignificant for system-initiated recommendations. The index of moderated mediation confirmed that the indirect effects significantly differed between user-initiated and system-initiated recommendations, β = -.23, SE = .13, 95%CI [-.51, -.01]. The test also demonstrated that user-initiated recommendations had a significant indirect effect on adherence to recommendations through perceived control for conversational recommender agents, β = -.25, SE = .10, 95%CI [-.47, -.07], yet the effect was insignificant for web recommender platforms. The index of moderated mediation confirmed that the indirect effects significantly differed between conversational recommender agents and web recommender platforms, β = -.23, SE = .13, 95%CI [-.50, -.01].

Mediated by trustworthiness. The test revealed that there were no significant indirect effects between the platform's anthropomorphic cues on adherence to the recommendations through trustworthiness for both user-initiated and system-initiated recommendations. However, user-initiated recommendations showed significant positive indirect effects on adherence to the recommendations through trustworthiness for conversational recommender agents, β = -.34, SE = .15, 95%CI [-.68, -.73], and web recommender platforms, β = -.33, SE = .16, 95%CI [-.67, -.03]. The index of moderated mediation demonstrated that the indirect effects did not significantly differ between conversational recommender agents and web recommender platforms, β = -.02, SE = .20, 95%CI [-.45, .37].

Mediated by perceived risk. The test revealed that there were no significant indirect effects between the platform's anthropomorphic cues on adherence to recommendations through perceived risk for both user-initiated and system-initiated recommendations. However, the test did find that system-initiated recommendations had a significant negative indirect effect on adherence to recommendations through perceived risk for conversational recommender agents, β = .25, SE = .12, 95%CI [.04, .52], and web recommender platforms, β = .13, SE = .08, 95%CI [.01, .32]. The index of moderated mediation demonstrated that the indirect effects did not significantly differ between conversational recommender agents and web recommender platforms, β = .11, SE = .10, 95%CI [-.03, .35].

4 DISCUSSION AND CONCLUSIONS

The study assessed the extent to which recommender systems' anthropomorphic cues and the type of recommendations provided influenced users' perceptions of control, trustworthiness, and the risk of using it. The study examined how these perceptions, in turn, influence users' adherence to the recommendations. Conversational recommender agents are widely available online, yet there is limited knowledge regarding the persuasive implications of their anthropomorphic cues on users' resistance to the platform and the provided recommendations. Moreover, there are gaps in the literature concerning proactive and reactive information disclosure in online marketing settings, especially when applied to conversational recommender agents. The study, thus, aimed to contribute to the understanding of the influences anthropomorphic cues have on users' resistance to recommender systems. The results of an online experiment with conversational recommender agents and web recommender platforms that provided user-initiated or system-initiated recommendations yielded interesting findings on the matter.

The first key finding indicates that when receiving user-initiated recommendations from a recommender agent, compared to system-initiated recommendations, one will be more likely to adhere to the recommendation, perceive to be in more control, and perceive the recommender system to be more trustworthy and less risky. In turn, adherence to the recommendations is based on perceived control, trustworthiness, and perceived risk. The second key finding indicates that when receiving user-initiated recommendations from a conversational recommender agent, compared to a web recommender platform, one would be more likely to adhere to the recommendations and perceive to be in more control. In turn, one will also be more likely to adhere to the recommendations based on the perceived control.

These findings are meaningful in different aspects. First, in line with mind processing theory [30, 34, 80, 81], which explains that people ascribe mental capacities to anthropomorphic nonhuman entities and then react to and evaluate these based on their moral judgments and values, users might have perceived and evaluated conversational recommender agents and the recommendations provided based on the moral value of the agent's actions. It provides evidence for the importance of conversational recommender agents, and artificial agents in general, to sustain a positive moral mentality in their actions, as it can reduce users' resistance when anthropomorphic cues are available. This validates earlier research on conversational recommender agents that demonstrated users' positive reactions to user-initiated recommendations [20]. Accordingly, it can be said that anthropomorphic cues could trigger positive and persuasive reactions when the recommender agent's actions, and mentality conform to people's inherent social roles and norms.

These findings also extend the theoretical scope of disclosure with conversational recommender agents. As users ascribed meaning to the recommender agent's actions, their disclosure to the recommender agent followed the expected social norms of interpersonal relations [1, 44, 61]. When the disclosure was reactive and forced, it was reflected in users' resistance to the platform and the recommendations. On the contrary, proactive disclosures of users to conversational recommender agents amplified users' positive perceptions of the platform and their adherence to the recommendations. This supports earlier findings that demonstrated negative users' reactions to system-initiated recommendations by conversational recommender agents (e.g., [48, 67, 71]). It can be implied from this study's results that anthropomorphic cues can also trigger negative reactions when the recommender agent's actions and mentality do not conform to people's inherent social roles and norms.

One additional key finding of the study should be taken into consideration when addressing the negative attributions of anthropomorphic cues. While it was expected that receiving system-initiated recommendations would lead users to demonstrate higher levels of resistance towards conversational recommender agents than

Table 4: Conditional indirect effects

		Perceived control		Trustworthiness		Perceived risk	
		β	95% CI	β	95% CI	β	95% CI
Anthropomorphic cues	User-initiated	0.18 (0.09)	0.03, 0.38	0.03 (0.14)	-0.23, 0.32	-0.05 (0.06)	-0.21, 0.05
	System-initiated	-0.05 (0.09)	-0.23, 0.12	0.01 (0.15)	-0.29, 0.31	0.06 (0.07)	-0.05, 0.22
Type of recommendations	Recommender Agent	-0.25 (0.10)	-0.48, -0.07	-0.34 (0.15)	-0.68, -0.07	0.25 (0.12)	0.03, 0.51
	Web Recommender Platform	-0.02 (0.08)	-0.19, 0.15	-0.33 (0.16)	-0.66, -0.03	0.13 (0.08)	0.01, 0.33

towards web recommender platforms, there were no differences between the two. Accordingly, it should be stressed that when the recommender agent's actions and mentality do not conform to people's inherent social roles and norms, users reacted to it as they would react to a recommender system that lacks anthropomorphic cues (i.e., web recommender platform). However, it could be that the concepts measured in this study are being evaluated differently when addressed to two different systems. Hence, risk, trust, and control might be understood differently when addressed to a conversational recommender system compared to a web recommender platform. See [47] for a similar discussion addressed to the concept of intelligence being addressed to a conversational recommender agent compared to a web recommender platform.

The last key finding of the study indicates that when receiving system-initiated recommendations from a web recommender platform, compared to user-initiated recommendations, there were no differences in users' perceived control and adherence to the recommendations. However, in this case, one will perceive the platform as less trustworthy and risker, and in turn, would be less likely to adhere to the recommendations. Moreover, when receiving user-initiated recommendations, there were no differences between the platforms regarding users' perceptions of trust or risk. These findings contradict earlier studies (e.g., [8, 10, 13, 35, 43]) that addressed online marketing procedures under the frameworks of social exchange theory [40] and privacy paradox [7], where users evaluate an exchange based on cost and reward cues [29, 40, 54–56]. A potential explanation could be that users need more systematic cues to evaluate the recommendations provided by web recommender platforms, as they look for pieces of information to assess the recommendations [14, 18, 27] in terms of costs and rewards.

Based on the findings of this study, it can be argued that when web recommender platforms lack sufficient cues to indicate the reward from the exchange (e.g., users' ratings, distance, users' reviews), users are limited in their evaluations and are prone to pick up on cues indicating the cost (e.g., disclosure). Therefore, users demonstrated higher resistance to system-initiated recommendations, compared to user-initiated recommendations, when using web recommender platforms. Nonetheless, future research should refine these results by evaluating user resistance to web recommender systems when cues indicating rewards from the exchange are presented against cues indicating the costs. These findings highlight that, while anthropomorphic cues can contribute to interactions with recommender systems and reduce potential resistance, the type of recommendation provided has a substantial impact on resistance. This aligns with earlier research that has addressed the persuasive implications of tailoring techniques and demonstrated the differences between customization and personalization (e.g., [4, 6, 17, 45, 46, 77–79]). It can, thus, be concluded that users' positive experiences when using recommender systems and adhering to recommendations are conditional based on recommendations being user-initiated and in line with their proactive disclosure. When the recommender system demonstrates anthropomorphic cues, the positive influence of user-initiated recommendations can be amplified, reducing users' potential resistance toward the platform and the recommendations.

There are several limitations to take into consideration. First, the use of simulated recommender systems in a single-treatment online experimental design; participants used recommender platforms that were designed specifically for this study. Being a hypothetical simulation, participants' engagement might have been limited such that they lacked the internal motivations to be engaged in a simulated commercial behaviour that has no impact on their life outside of the study. Participants were given recommendations about fictional restaurants, and accordingly, their reaction to the manipulations could be restrained and not reflective of their potential reactions in commercial settings. Moreover, while the act of personalization was explicitly stressed to trigger reactions, the recommender systems were restricted from retrieving actual user information to personalize recommendations. These simulations might not correspond with realistic personalization situations or trigger precisely the same reactions that users would demonstrate in naturalistic settings with a commercial recommender system. However, using these simulations allows us to study resistance to recommender systems while complying with ethical considerations and not collecting participants' personal information. Furthermore, the use of a single-treatment online experimental design allowed for the collection of fair sample size and minimal dropout rate. To reduce any potential threat to the internal validity of the study, participants' perceptions of the manipulations' realism were controlled in both manipulation checks, and when diagnosing the sample for outliers. Future research could target these limitations and extend these findings by employing a longitudinal design using agent or web simulations. By conducting the study over time in more naturalistic settings, the simulations could correspond to users' expectations and reflect their reality. Also, it could elicit information from participants that could be used for simulating conditions of system-initiated recommendations in more individualistic terms without compromising participants' privacy in an ethical and responsible way (see [57]).

ACKNOWLEDGMENTS

We gratefully acknowledge funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie to ENTWINE, the European Training Network on Informal Care (grant agreement No 814072).

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