

COMP 3647 Human-Al Interaction Design

Topic 9
Case Studies of LLMA:
Customer Service Chatbots

Prof. Effie L-C Law

Overview

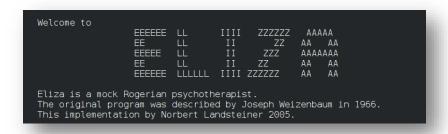
- Basics of Conversational Agents (CA)/Chatbots
- Chatbots for Customer Services
- Factors for Trust in Chatbots
- Impact of Online Banking on Older Adults
- Implications for the Design of Chatbots for Older Adults



Conversation is the Interface

As technology gets smarter, and more anticipatory of our wants and intent, the interface gets smaller and smaller until it disappears.

A Very Brief History of Chatbots



Keyword matching
Minimal context identification

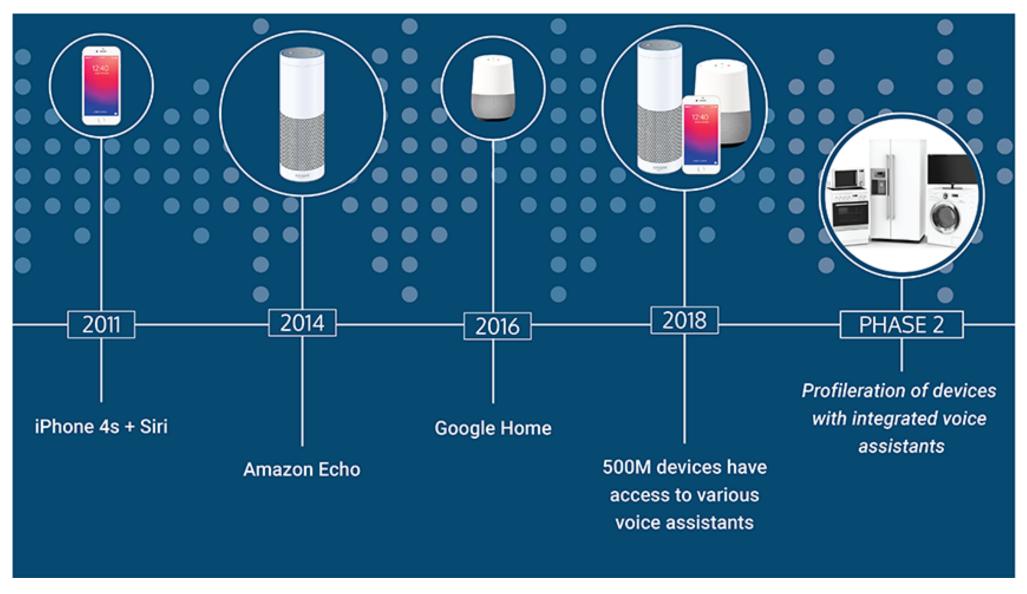


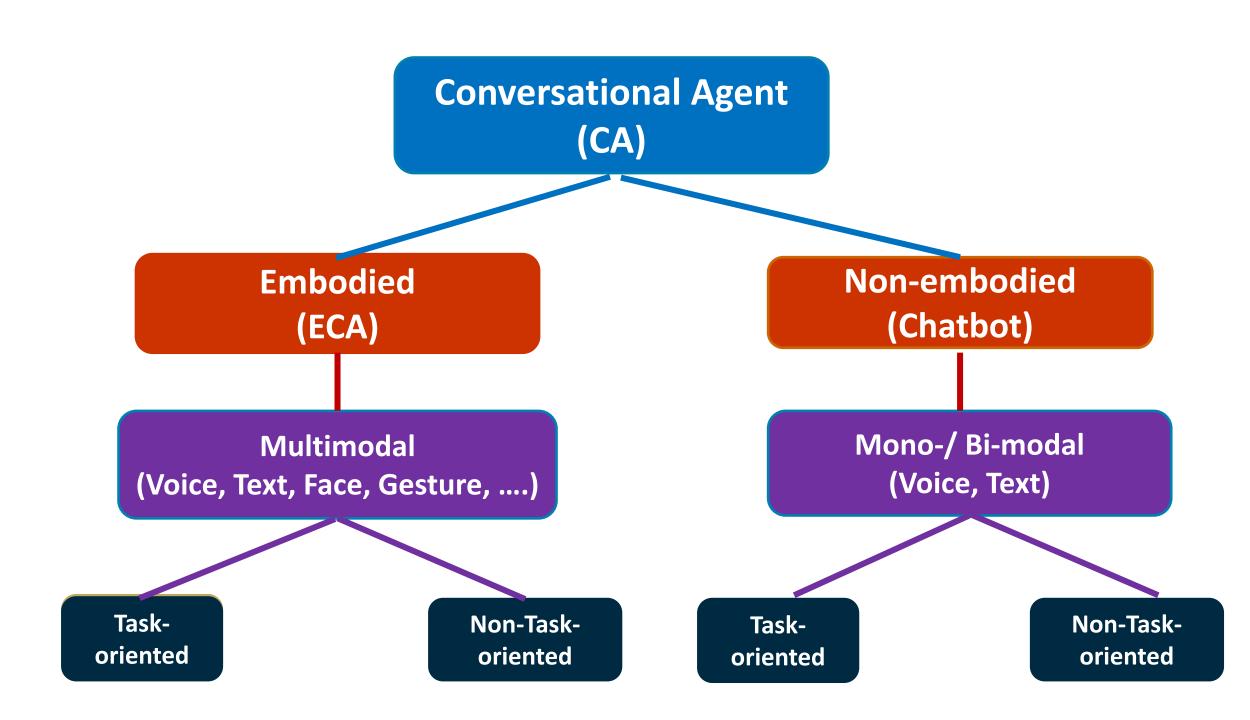
Conversational capability
Artificial Intelligence Markup Language (AIML)

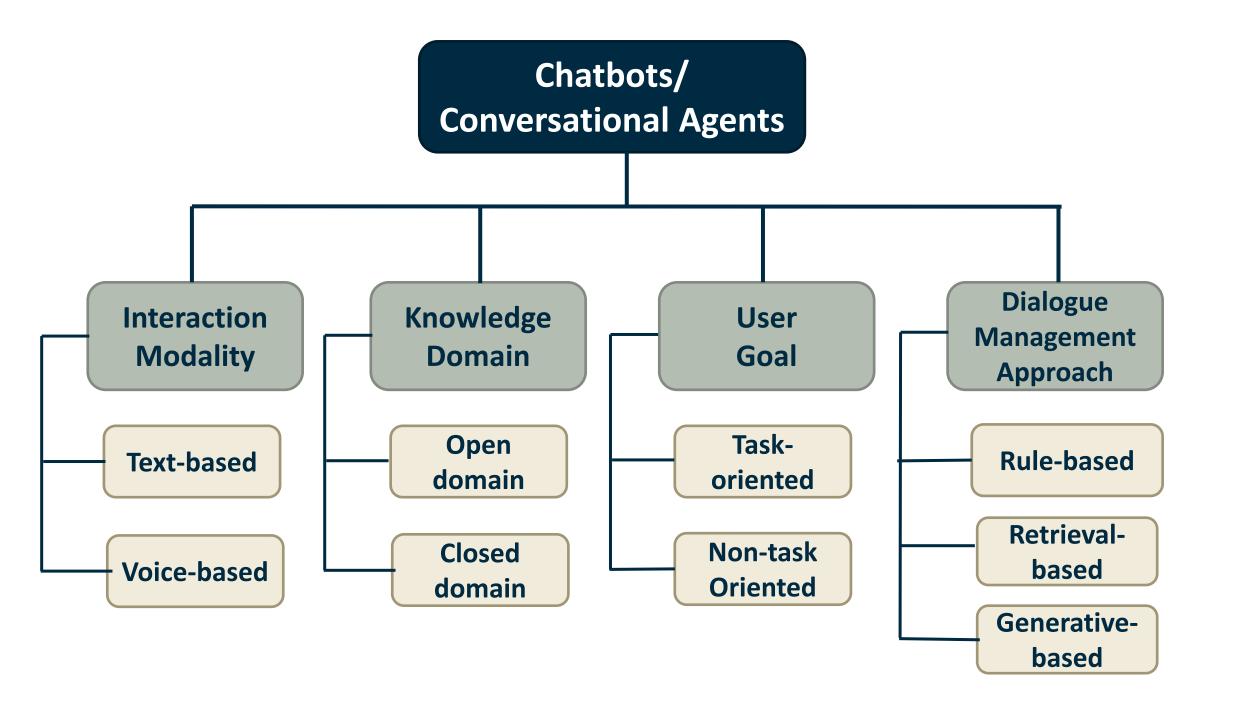


Machine Learning-powered Deep Neural Networks

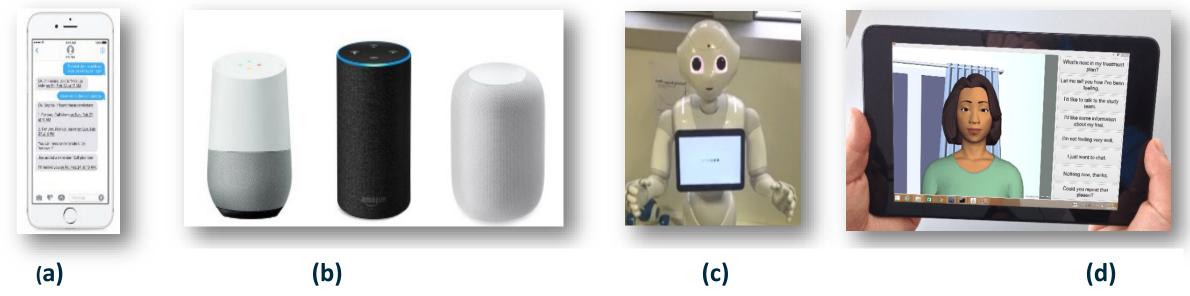
Conversational/Voice User Interface (VUI)







Types of CAs

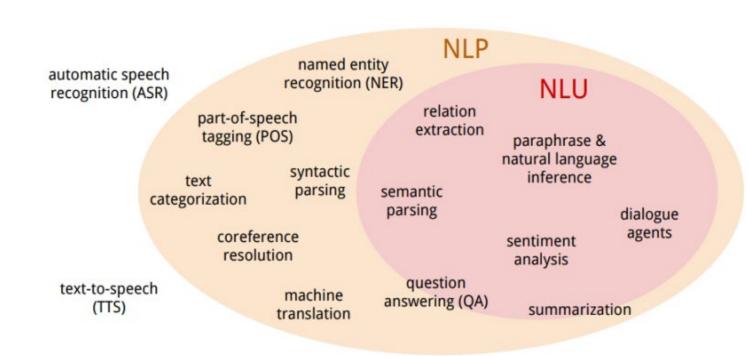


(a) Non-embodied text-based CA; (b) Non-embodied voice-based CA; (c) Embodied CA, multimodal social robot; (d) Embodied CA, multimodal mobile CA

Natural Language (NLP/U/G) Processing/Understanding/Generation

- NLP: unstructured data

 a structured data format
 for understanding and
 response formulation
- NLU: machine reading comprehension to identify the intended meaning of a verbal expression
- NLG: construction of a verbal expression by a machine based on a given dataset



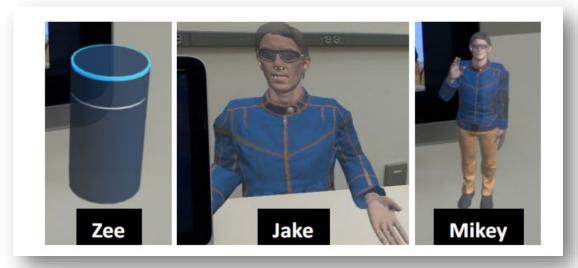
Embodied CA: Human-Robot Interaction (HRI)

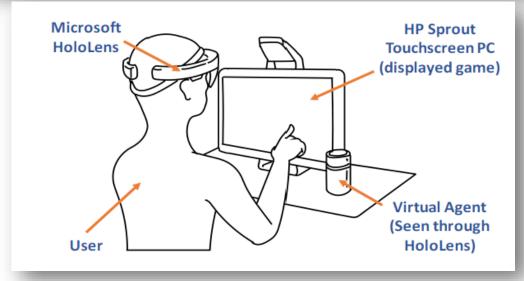
User (dis)engagement

- Behavioural signal detection: verbal (text/voice); non-verbal (gaze, posture, gesture)
- Explicit self-reported measures: presence, relatability, realism, usefulness, trust
- Implicit feedback: dwell time, number/length of utterance

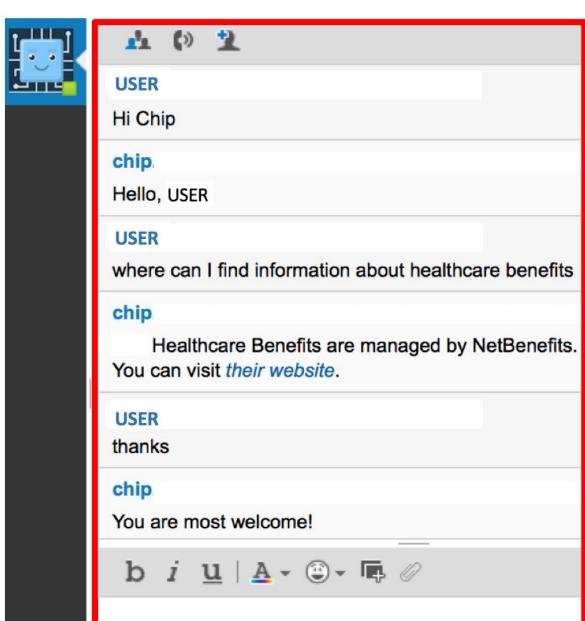
Real-time algorithmic adaptations

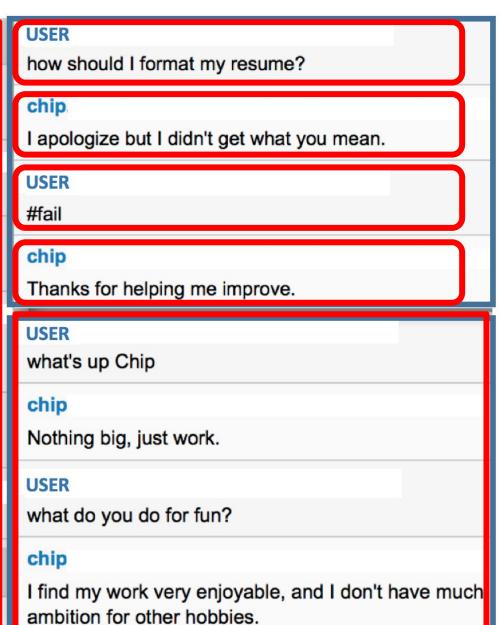
- User goals/needs
- Agent representation
- Utterance presentation





Non-Embodied QA Chatbots: Watson Assistant





Evaluation of the QA Chabot (Liao et al. CHI 2018)

Prediction of user satisfaction

- Conversational Act: Natural language classifiers
- Lexical features: Bag-of-words (tri-gram)

Satisfaction with Functionality

- Positive:
 - Formal questions "What/Where/Which/How...."
- Negative:
 - Sarcastic remark: "You are smart"
 - Agent ability check: "What can you do?" "Can you do ...?"
 - o Closing: "bye".."

Seeking Playfulness

- Chit-chat (off topic)
- Asking about agent's trait, asking about agent's status, talking about oneself
- Testing intelligence "search information about my boss"
- Second-person pronoun "how are you?"

Conversational NLC1

OPENING

CLOSING

COMPLIMENT

ACKNOWLEDGE

COMPLAINTS

FEEDBACK

AGENT STATUS

CHITCHAT

AGENT TRAIT

CHITCHAT

AGENT ABIL-

ITY CHECK

OFF TOPIC RE-

QUEST

ABOUT ME





Effects of Humanlikeness and Conversational Breakdown on Trust in Chatbots for Customer Service

Effie Lai-Chong Law, Durham University, UK
Asbjørn Følstad, SINTEF, Norway
Nena van As, boost.ai, Norway









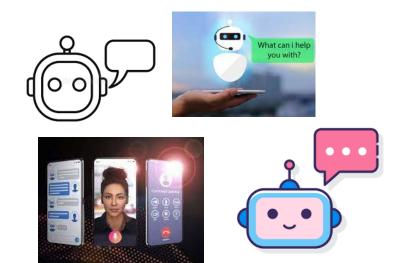




Motivation

What are Customer Service Chatbots?

Chatbots are Al-powered software agents that interact with users through natural language and may, hence, be seen as a supplement to chat-based service offered by human support personnel.



What are Applications?

- Retail and e-commerce
- Travel and hospitality
- Banking, finance, and fintech
- Healthcare
- Media and entertainment
- Education

• ...



https://research.aimultiple.com/business-chatbot/



Revising *User Model* → Calibrating Trustworthiness





Chatbot as Interactive Tool





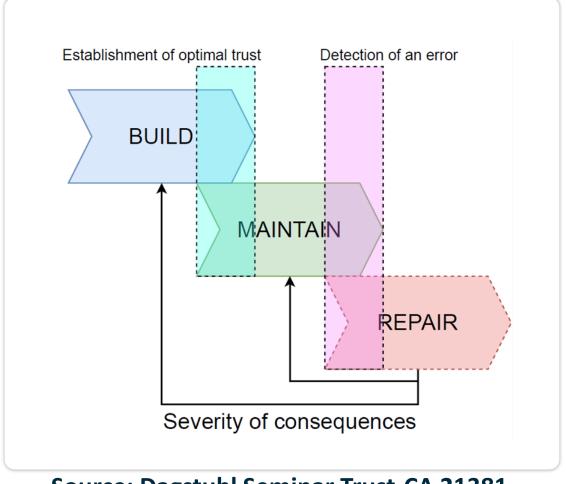
Interaction & Curation
"It is ok. But how about this?"

Revising Mental Model → Calibrating Trust



What is Trust?

- Trust: the willingness of a trustor to accept vulnerability (risk) based on positive expectations of the intentions or behaviour of the other (Rousseau et al., 1998)
- Trust depends on user perceptions of system functionality (competence), helpfulness (benevolence), and reliability (integrity) (Mcknight et al., 2011)
- Trust is hard earned and easily lost.



Source: Dagstuhl Seminar Trust-CA 21381



Research Questions

- Are chatbots' humanlike features as important for trust as their ability to reliably provide support?
 - O Design: conversational style, visual representation, informal language, features hinting at chatbot intelligence (Go & Sundar, 2019)
 - Impact: hedonic user experience, brand perception, user sentiment, user compliance, transaction conversion, and intention to use.
- Is trust dominated by the chatbot's conversational performance rather than their humanlikeness?
 - The chatbot's ability to provide relevant and helpful responses to users' requests.
 - Chatbot productivity, efficiency and effectiveness → Chatbot user engagement (Brandtzaeg and Følstad, 2017)
- Does chatbot humanlikeness strengthen in the face of performance issues? trust resilience
 - Trust resilience: upkeep of trust in spite of undesirable system outcomes (De Visser et al., 2016)



Method

2 x 3 factorial experimental design with two Independent Variables (IVs):

- Humanlikeness (low vs. high)
- Conversational performance (No breakdown, Breakdown with Repair, Breakdown without Repair)

CHATBOT FOR CUSTOMER SERVICE

On this page, you find a chatbot for customer service. The chatbot represents a fictitious consumer bank called Boost Bank.

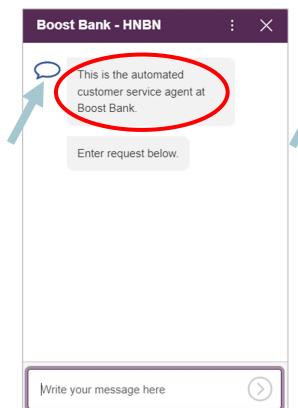
Your first task is to use the chatbot to get information about the following:

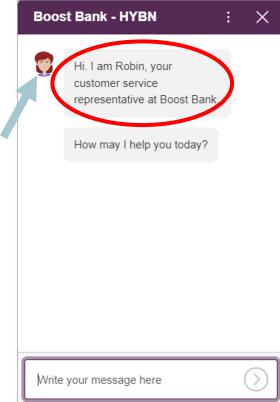
- First, the Boost Bank loan interest rates
- Second, how to apply for a loan at Boost Bank
- Finally, making an appointment with a bank advisor at Boost Bank

When you have found the information, the chatbot will provide you a link to a questionnaire for your feedback.

You may also at any time send the message "stop" to the chatbot to end the dialogue and move on to the questionnaire.

Open the chatbot by clicking the icon in the lower right corner.







If the loan is for more than 70% of the total value,

interest rates are slightly higher at 4%



Humanlike	Non-Humanlike
Chatbot: Hi. I am Robin, your customer service representative	Chatbot: This is the automated customer service agent at Boost
at Boost Bank.	Bank.
How may I help you today?	Enter your request below.
User: Loan interest rate	User: Loan interest rate
Chatbot: I am happy to help you with loan interest rates. At	Chatbot: Boost Bank offers competitive loan interest rates. For
Boost Bank we are proud/happy to offer competitive interest	information, select one of the following.
rates. Which type of loan are you interested in?	- Home
- Home	- Vehicle
- Vehicle	- Flexible
- Flexible	User: [Clicks button]
User: [Clicks button]	Chatbot: Home / Vehicle / Flexible loan interest rates are as
Chatbot: Thank you. Let me give you a brief overview of our	follows:
Home / Vehicle / Flexible loan interest rates:	- Loans less than or equal to ≤70% of total value:
- If the loan is for 70% of the total value or less, you	interest rate 3%
get our best interest rate of 3%	- Loans greater than 70% of the total value: interest rate

4%

If chatbot does not understand:

Chatbot: I am sorry that I was not able to understand your question.

You may try to ask again using slightly different words. Please keep questions brief and to the point.

If chatbot understands the second time (With Repair)

[the regular conversation on "Apply for a loan"]

If chatbot does not understand – second time (No repair):

Chatbot: I am sorry, but it seems that I am not able to help you with this question.

Is there anything else I can help you with?



Chatbot: Request not identified.

Consider entering the request in other words. Requests should be brief and concise.

If chatbot understands the second time (With Repair)

[the regular conversation on "Apply for a loan"]

If chatbot does not understand – second time (No repair):

Chatbot: Unable to respond to request.

A new request may be entered.





Measures

Variable (nr. items)	Example item (7-point Likert scale)	Source
Trust General (3)	When in need of customer service, I feel I can depend on the chatbot	Lankton et al. (2015)
Task-specific Trust (3)	Considering the chatbot's answer on [Task 1/2/3], I feel I can depend on it.	Home-grown
TT1, TT2, TT3	I can rely on the support provided by the chatbot on [Task 1/2/3].	
	I feel I can count on the chatbot for questions on [Task 1/2/3]	
Trust Belief Reliability (3)	The chatbot is a very reliable solution	Lankton et al. (2015)
Social Presence (4)	I felt like I was engaged in an active dialogue with the chatbot	Laban & Araujo (2019)
Perceived	Machine like vs. Human-like (semantic differential)	Araujo (2021)
Anthropomorphism (3)		
Prior Chatbot Experience	Prior Use Preference (3): I frequently use chatbots for customer service	Home-grown
	Prior Satisfaction (3): I usually find chatbots for customer service pleasant to use	
	Prior Use Frequency (1)	
Demographic	Gender; Age; Country of residence; Education	Home-grown



Null Hypotheses

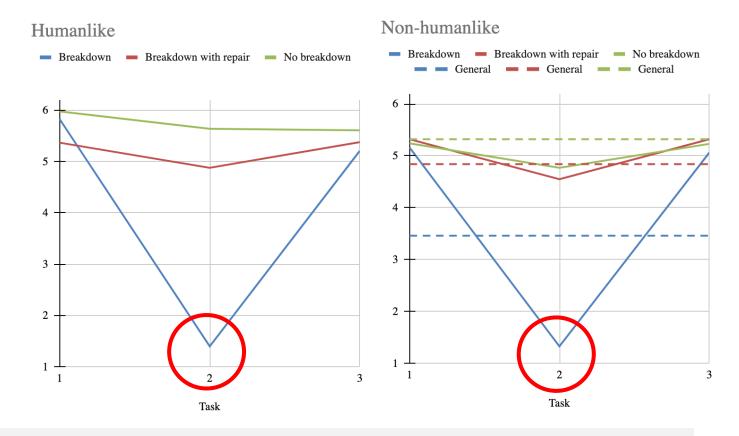
- Overall trust (OT) is the same across the six conditions.
- Task specific trust (TT) is the same...
 - For each task between conditions
 - For each task within conditions

	No Breakdown (n=77)	Breakdown with Repair (n=85)	Breakdown without Repair (n =89)
Humanlike (n=121)	Group 1 (n =39)	Group 2 (n =40)	Group 3 (n =42)
Non-humanlike (n=130)	Group 4 (n =38)	Group 5 (n =45)	Group 6 (n =47)



Results

- Breakdown severely impacts task-specific trust.
- Similar trend for general trust.
- Humanlike and non-humanlike conditions seem similar, especially in the breakdown conditions.



- First, the Boost Bank loan interest rates
- Second, how to apply for a loan at Boost Bank
- · Finally, making an appointment with a bank advisor at Boost Bank

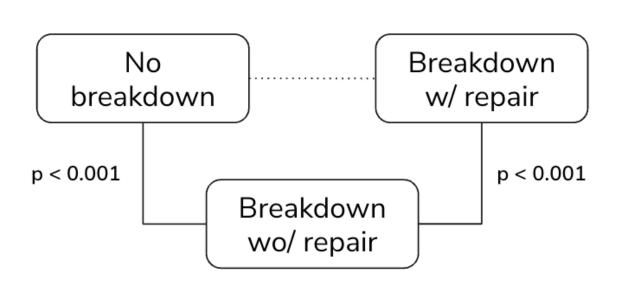


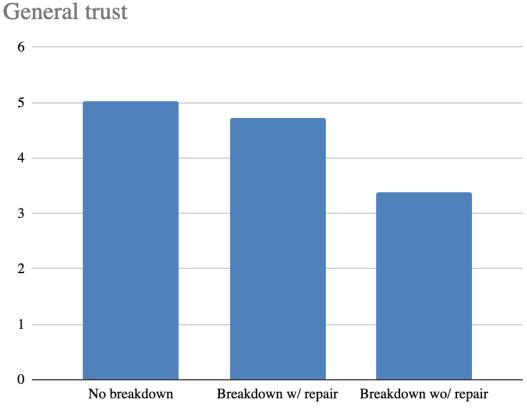
Analysis

- Both Humanlikeness and Conversational Performance have an effect on General Trust (GT) and Task-specific Trust (TT)
- For Task-specific Trust:
 - Humanlikeness only had effect on TT1.
 - Conversational performance only had effect on TT2.
 - TT3 not affected.

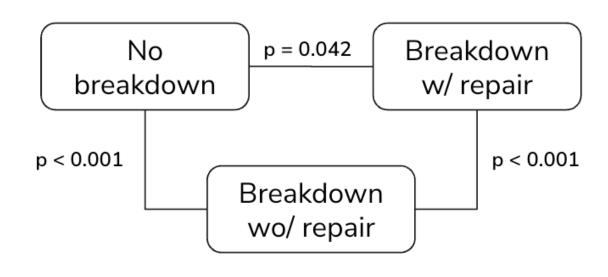
		GT	TT1	TT2	TT3
Humanlikeness	F(1,245)	4.617	8.802	2.902	1.149
	p	0.033	0.003	0.096	0.285
	η	0.18	0.035	0.025	0.015
Conversational performance	F(1,245)	36.98	0.87	210.91	0.840
	p	<0.001	0.422	<0.001	0.433
	η	0.23	0.007	0.21	0.007
Interaction Effect	F(1,245)	0.437	1.740	1.904	0.247
	p	0.647	0.178	0.151	0.781
	η	0.004	0.014	0.015	0.002

Conversational Performance on General Trust

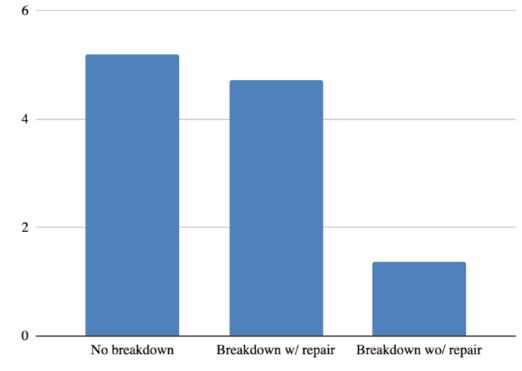




Conversational Performance on Task-Specific Trust (Task 2)



Task specific trust for task 2



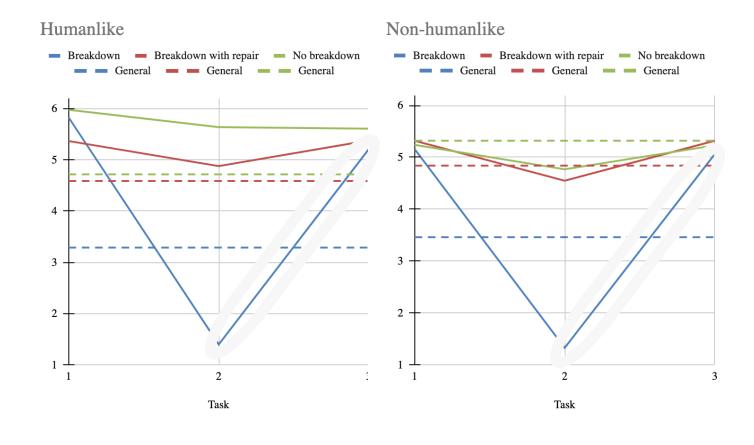
Discussion

Does chatbot humanlikeness strengthen trust resilience in the face of performance issues?

No!

Humanlikeness and
Conversational Performance
exerted their effect
independently of each other.

Recovery of trust from Task 2 to Task 3 is **NOT** stronger for the humanlike condition.



Discussion

Is trust dominated by the chatbot's conversational performance rather than their humanlikeness?

Yes!

Humanlikeness only impacted Task-specific Trust upon first encounter. After experience, no longer significant.

		GT	TT1	TT2	TT3
Humanlikeness	η	0.18	0.035		
Conversational performance	η	0.23		0.21	
Level 1 : 2	t(160)			2.12 0.042	
Level 2 : 3	t(172)	6.85 <0.001		17.81 <0.001	
Level 1:3	t(164) p	7.71 <0.001		19.22 <0.001	

Practical Importance of Repair

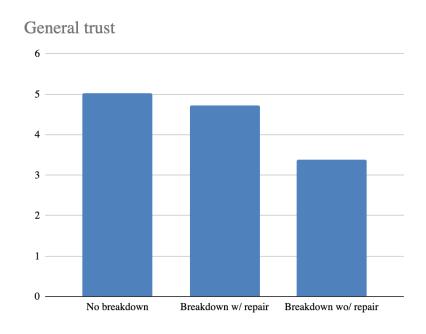
Strength of repair: as if no breakdown occurred at all!

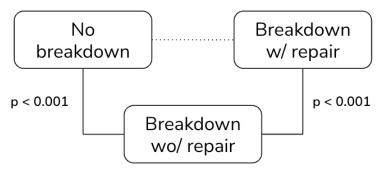
Trust resilience

Prioritisation:

- Anticipate on failure
- Design for repair
 - with/without apology
 - type of apology



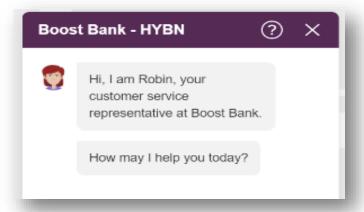


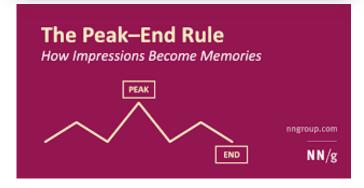


Limitations & Implications

- Humanlikeness
 - Appearance: Modality, Embodiment, Realism
 - Humanlike chatbot conversations (Jain et al. 2017)
 - Clarify the chatbot capabilities (disclosure)
 - Sustain the context of the talks (context-awareness)
 - Acknowledge dialog failures (with/without apology)
 - End the conversations with grace (Peak-End effect)
- > Task criticality
 - Perceived relevance and riskiness
 - Order effect

- · First, the Boost Bank loan interest rates
- Second, how to apply for a loan at Boost Bank
- Finally, making an appointment with a bank advisor at Boost Bank







Effects of Prior Experience, Gender, and Age on Trust in a Banking Chatbot with(out) Breakdown and Repair

Effie Lai-Chong Law, Durham University, UK **Nena van As**, boost.ai, Norway **Asbjørn Følstad**, SINTEF, Norway













Research Question

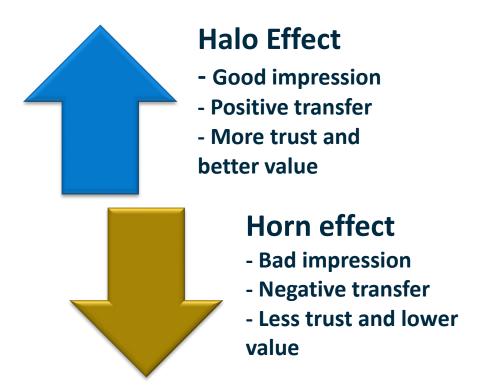
What is the respective effect of

- (a) prior experience
- (b) gender
- (c) age

on the perceived trust and interaction qualities of the chatbots characterised by humanlikeness and conversational performance?

Prior Experience on Trust

Impressions formed in previous interactions with humans/ products/ services can shape people's attitudes and behaviours in subsequent encounters with entities having some similar traits: Cognitive Bias



Beauty and Usability in HCI Marc Hassenzahl (2004)

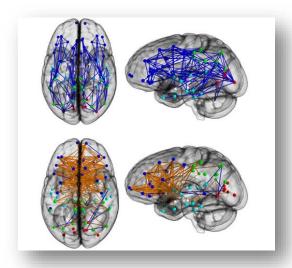
Marketing research
Marie-Sophie Schönitz (2019)

Gender Effect on Trust

- Men tend to trust interaction objects (human, non-human) *more* than women (Buchan et al., 2008; Wu et al., 2020)
- Women more sensitive to social risk while trusting
 (Wu et al., 2020)
- Gender differences in predisposition to trust (Rachid, 2020) and trust dynamics (Haselhuhn et al 2015)
 - following a trust violation, women less likely to lose trust and more likely to restore trust in a transgressor than men
- Gender of chatbot avatars
 - female avatar more likely forgiven for error (Toader et al 2019)
 - online shopping: no gender effect (Kasilingam 2020)
 - Student support chatbot: no gender effect (Pesonen 2021)



The Neurobiology of Trust. Scientific American (2008)

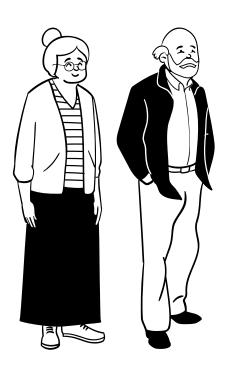


https://blog.culturaldetective.com/2013/12/17/new-brain-study-illustrates-gender-differences/

Age Effect on Trust

- Chatbot usefulness
- Chatbot enjoyment
- Use chatbot to avoid human contact
- Effort invested in using chatbot
- Appreciate chatbot with human touch (Goot & Pilgrim 2019)





Method

- Between-subject experimental studies with six conditions
- A set of measures on trust and demographic variables

	No Breakdown (n=77)	Breakdown with Repair (n=85)	Breakdown without Repair (n =89)
Humanlike (n=121)	Group 1 (n =39)	Group 2 (n =40)	Group 3 (n =42)
Non-humanlike (n=130)	Group 4 (n =38)	Group 5 (n =45)	Group 6 (n =47)

Variable (nr. items)	Example item (7-point Likert scale)	Source
Trust General (3)	When in need of customer service, I feel I can depend on the chatbot	Lankton et al. (2015)
Task-specific Trust (3)	Considering the chatbot's answer on [Task 1/2/3], I feel I can depend on it.	Home-grown
TT1, TT2, TT3	I can rely on the support provided by the chatbot on [Task 1/2/3].	
	I feel I can count on the chathot for questions on [Task 1/2/3]	
Demographic	Gender; Age; Country of residence; Education	Home-grown

Demographic variables

- Prior Use Preference
 - when choices available, chatbot is preferred
- Prior Chatbot Satisfaction
 - perceived efficiency,
 effectiveness and pleasure
 of using the chatbot for the service

7-point Likert Scale (1: Strongly Disagreed, 7 Strongly Agreed)

Prior Chatbot	Prior Use Preference (PF)					
Experience	PF1: I frequently use chatbots for customer service PF2: I use chatbots for customer service when this is provided as a service alternative PF3: I have used chatbots for customer service for a long time					
	Prior Chatbot Satisfaction (SAT) SAT1: Chatbots for customer service typically provide good help SAT2: In general, chatbots for customer service are an					
	efficient way to get support SAT3: I usually find chatbots for customer service pleasant to use.					
	Prior Use Frequency (FQ)					
	Five options:					
	More than 10 times					
	• 5-10 times					
	• 3-4 times					
	1-2 timesNever					
Demographic	Gender (female, male, prefer not to say) Age (free text) Country of residence (free text)					

Education (three options)

Results: Prior Use Preference

3*2*3 ANOVAs ([Prior variables]*Humanlikeness*Conversational Performance)

Group	Range	n	Overall Trust
Low	1.00-3.67	91	3.71 (.16)
Middle	3.68-5.33	74	4.08 (.17)
High	5.34-7.00	86	5.13 (.14)

General Trust: $F_{(2,233)} = 21.920$, p < .001, $\eta^2 = .158$ Significant



Results: Prior Use Frequency

3*2*3 ANOVAs ([Prior variables]*Humanlikeness*Conversational Performance)

Group	Range	n	Overall Trust
Low	<5 times	64	3.95 (0.19)
Middle	5-10 times	90	4.44 (0.16)
High	>10 times	97	4.44 (0.16)

General Trust: $F_{(2,233)} = 1.917$, p = .149, $\eta^2 = .016$ *Non-significant*



Results: Prior Chatbot Satisfaction

3*2*3 ANOVAs ([Prior variables]*Humanlikeness*Conversational Performance)

Group	Range	n	Overall Trust
Low	1.00 -3.67	91	3.28 (0.14)
Middle	3.68 -5.33	74	4.32 (0.13)
High	5.34 -7,00	86	5.41 (0.14)

General Trust: $F_{(2,233)} = 65.456$, p < .001, $\eta^2 = .360$ Significant



Correlations among Prior Variables

- People preferred using chatbots for customer service tended to be satisfied with them.
- For Female and Older users, the more they used them, the more unsatisfied they were with them.

	All	Female	Male	Younger	Middle	Older
	N = 251	N=178	N=69	N=112	N=72	N=67
Satisfaction vs.	0.64	0.640	0.624	0.677	0.607	0.611
Preference	<i>p</i> <.001					
Satisfaction vs.	-0.195	-0.230	-0.083	-0.168	-0.210	-0.251
Frequency	p = .002	p=.002	p=.496	p=.076	p=.076	p=.041



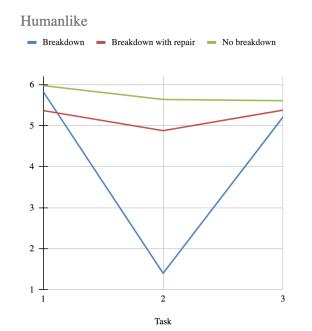
Results: Gender

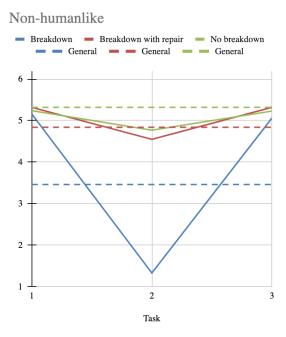
2*2*3 ANOVA (Gender * Humanlikeness * Conversational Performance)

- General trust: No significant difference between female and male
- **Trust Resilience**: No significant changes in *Diff(TT1-TT2) or Diff (TT2-TT3)* for male and female, both trust resilient.

	Female					
	Humanlike				Non-humanlike	
Conversational Performance	TT1 TT2 TT3 TT1 TT2 T					TT3
No Breakdown	6.01	5.77	5.74	5.15	4.91	5.35
Breakdown with Repair	5.27	4.76	5.31	5.37	4.66	5.32
Breakdown without Repair	6.08	1.45	5.22	5.06	1.1	4.94
	Mala					

		Male						
	Humanlike Non-humanlik					like		
Conversational Performance	TT1	TT2	TT3	TT1	TT2	TT3		
No Breakdown	5.86	5.05	5	5.4	4.53	5.2		
Breakdown with Repair	5.69	5.21	5.59	5.21	4.31	0.31		
Breakdown without Repair	5.5	1.38	5.07	5.52	2.09	5.45		





Results: Age & General Trust

3*2*3 ANOVAs (Age*Humanlikeness*Conversational Performance)

Group	Range (years)	n	Overall Trust
Younger	18 - 30	112	4.21 (1.61)
Middle	31 - 40	72	4.39 (1.50)
Older	41 - 68	67	4.41 (1.55)

General Trust: $F_{(2,231)}$ =.759, p =.469 non-significant

Results: Age & Trust Resilience

Three-way interaction effects
(Age*Conversational Performance*
Humanlikeness) for trust differences were significant:

- $Diff(TT1-TT2) (F_{(4,233)} = 3.57, p = 0.008)$
- $Diff(TT2-TT3) (F_{(4,233)} = 2.49, p = .044)$

	Young	ger					
	Humanlike Non-humanlike						
Conversational Performance	TT1	TT2	TT3	TT1	TT2	TT3	
No Breakdown	5.87	5.56	5.69	4.88	4.59	4.90	
Breakdown with Repair	5.15	4.75	5.32	5.20	3.8	4.98	
Breakdown without Repair	5.96	1.23	5.32	4.85	1.24	4.85	
	Middl	e					
	Humanlike Non-humanlike						
Conversational Performance	TT1	TT2	TT3	TT1	TT2	TT3	
No Breakdown	6.03	5.93	5.73	5.34	4.79	5.49	
Breakdown with Repair	5.89	4.83	5.39	5.54	5.28	5.72	
Breakdown without Repair	6.00	1.17	5.64	5.25	1.52	5.00	
	Older						
		Humanlike		Non-hui	manlike		
Conversational Performance	TT1	TT2	TT3	TT1	TT2	TT3	
No Breakdown	6.13	5.47	5.33	5.83	5.13	5.5	
Breakdown with Repair	5.48	5.10	5.48	5.24	4.97	5.42	
Breakdown without Repair	5.42	1.97	4.57	5.49	1.23	5.44	

The three age groups changed the level of trust from task to task significantly under different chatbot conditions.

Implications

Prior experience: The halo or horn effect on trust (of positive/negative transfer) from previous chatbot experiences

- To understand the experience users bring with them
- To design prompts or marketing strategies to address these earlier experiences.

Gender: No significant difference in trust as observed in human-human interaction

 To reconsider the assumption that models on human trust in AI-powered systems can be grounded in their counterparts on interpersonal trust

Age: No significant main effect, but significant interaction effects

Older adults may appreciate more emotional than practical value from chatbot interactions



Conversational Agents for Older Adults (CA4OA)

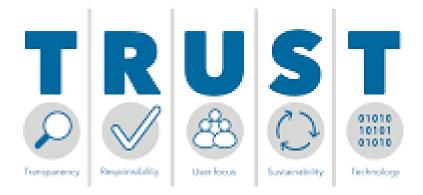
Co-designing *Inclusive* and *Trustworthy* Conversational Agents on Basic Services with Older Adults

April 2023 – June 2024



Motivation

- Chatbots for customer service: Healthcare, Banking, Entertainment...
- Low adoption among older adults: Trust in emerging technology
- Distrust → Underuse → Digital Marginalisation
- Mistrust → Overuse → Digital Exploitation



Transparency
Responsibility
User-focus
Sustainability
Technology

https://www.rd-alliance.org/trust-principles-rda-community-effort

Online Banking

How many bank branches have closed since 2015? **5,579**, at a rate of around 54 per month.

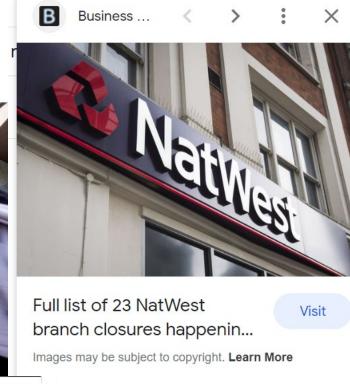


'elderly and vulnerable'









Mind the Gap

FCA: Basic financial services are available to vulnerable, digitally excluded parts of society in physical branches rather than online only.

Financial Conduct Authority (FCA) (2022). Branch and ATM closures or conversions. *Finalised Guidance*, *FG 22/6*, October 2022.

The critical gap between online banking services provision and user adoption can be bridged by improving CUSTOMERS' trust in digital tools.



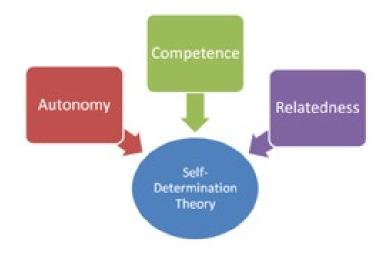






Trust & Older Adults' Attributes

- Three basic needs (SDT)
 - Autonomy
 - Competence
 - Relatedness
- Loneliness (Lieberz et al., 2021)
 - Interpersonal trust
 - Human-robot trust
- Attitudes
 - Confidence, prior experience in technology
 - Prejudice towards technology: Intergroup Contact Theory (Gordon Allport, 1954; Haggadone et al. 2021)









Trust by Design for Conversational Agent (CA)

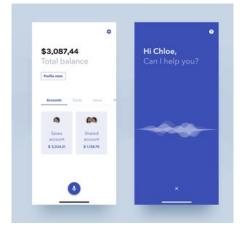


- Varied extents of CA modality, embodiment and anthropomorphism: 2D/3D, unimodal/ multimodal, and realism (low/high avatar fidelity)
- Conversation flows to match older adults' mental models (i.e., human-Al metaphors) of CAs; the transferability of human-human to human-agent communication.
- Conversation patterns of CAs to match older adults' age, gender, physical & psychological conditions
- Varied presentations of alerts to risks and breakdown repairs on older adults' trust in CAs.





https://www.allerin.com/blog/what-will-happen-when-ar-vr-and-chatbots-all-converge



https://dribbble.com/tags/bank_bot



https://www.superworldapp.com/content-hub/the-future-of-ai-chatbots-is-in-ar

Chatbot Design Requirements (Grudin & Jacques, 2019)

Human-centred Design Approach

- 1) investigating the strengths of different platforms and tools, and identifying user needs;
- setting a personality;
- determining task difficulty;
- 4) understanding the access environment and users' tendency to be forgiving of errors;
- 5) making amusing scripted responses;
- 6) making chatbots reveal their identity (disclosure);
- 7) iterating through small-scale user testing

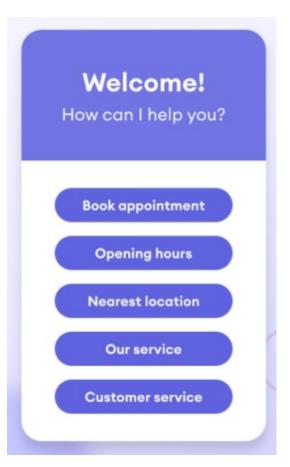


Text- vs. Button-based Interaction

- Custom buttons allow only a limited range of inputs, facilitating a decision-making process.
- Limiting the options, using easily navigable buttons rather than mobile keyboard makes conversations with

chatbots more accessible. (Ryu et al. 2020)





Method: Older-Adult-centred Design

- Enabling older adults of heterogeneous backgrounds to state their needs, preferences, and experiences of using CAs
- Qualitative Method: Contextual Inquiry and Participatory Design
 - Interviews
 - Focus groups
 - in situ observations
- Quantitative Method: Questionnaire to measure
 - Loneliness
 - Trust
 - \circ UX
 - Attitudes toward CAs
 - Intention to use
- Online banking services: issuing bank statements, checking account balance, transfer, bill payment, and cheque deposit

Summary

- Chatbots are increasingly impactful at all levels!
- Trust in chatbots for customer service mainly determined by their performance rather than humanlikeness.
- Trust in chatbots for customer service seems not gender-sensitive, but agesensitive.
- Older adults can become digitally marginalised when more and more essential services moving online.
- Make chatbots trustworthy; enable older adults to trust and use them.
- Ethics is of utmost importance
- Usable, useful, and safe ICT for older adults' wellbeing!



Questions?

