UNIVERSITÀ DEGLI STUDI DI GENOVA

Instagram Reactions to a Virtual Dining Companion: Qualitative Coding vs. Automated Sentiment Analysis

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Finanziato dall'Unione europea NextGenerationEU

Ministero dell'Università e della Ricerca

Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA

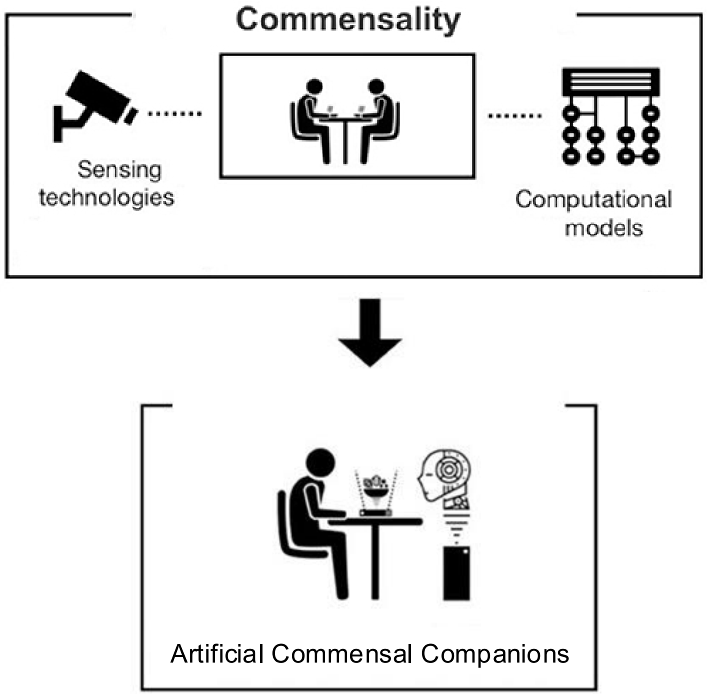
This work supported by the PRIN2022 project COCOA (D53D23008850001), funded by the Next Generation EU (NGEU) Programme, National Recovery and Resilience Plan (PNRR) and by the Italian Ministry of University and Research.

COmputational Models of COmmensality for artificial Agents

PRIN 2022

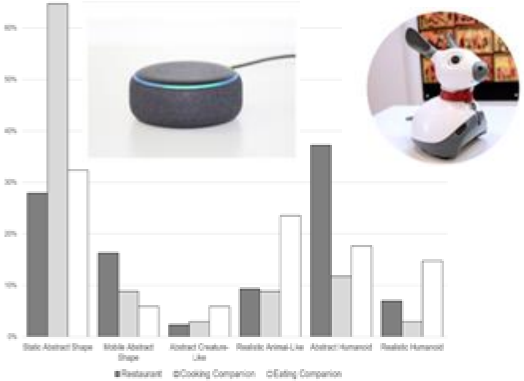
The project aims to:

- investigate human-human interactions in a commensal setting using state-of-the-art AI methods
- develop Artificial Commensal Companions (e.g., social robots) capable of engaging with human commensals



https://cocoa-research.github.io/

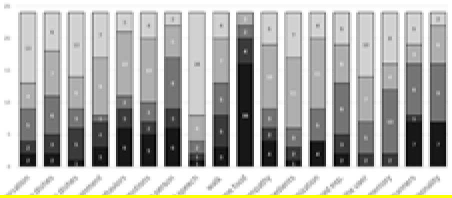
Previous works – questionaire



Online questionnaire composed of 98 items:

- focus on attitudes, expectations and concerns towards robotic companions in context of food and eating

- a broad array of aspects such as embodiment, appearance, skills, preferred ways of communication, risks and applications, and preferred social settings

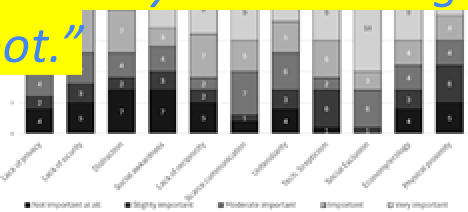


“It could be uncomfortable, if done in an open space with other people able to see that you are dining with a robot.”

Results:

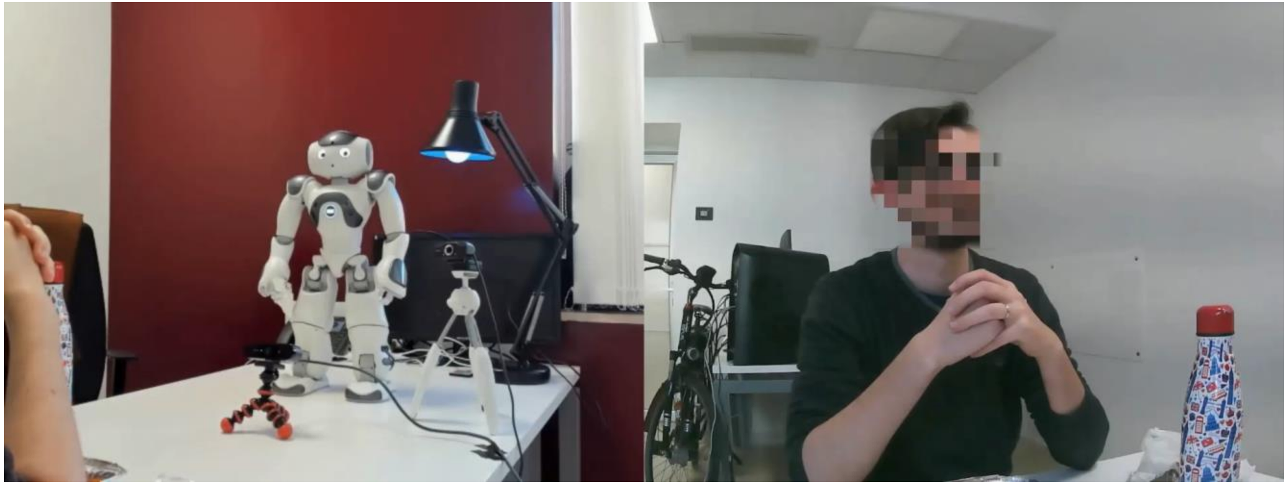
- preference for non-humanoid, possibly virtual, primarily servile agents that avoid personal topics

- certain skepticism: main concerns are related to social ostracism and alienation



Hoxha et al., 2024

Previous works – interaction with a robot



Twenty-two participants:

- unanimously enjoyed the interaction
- stated that they would prefer eating with a robot to eating alone

Requests:

- stronger personalization
- ability to discuss personal topics and interests
- ability to show empathy

Fong et al., 2025

Current study

Aim: to explore attitudes towards VR companions

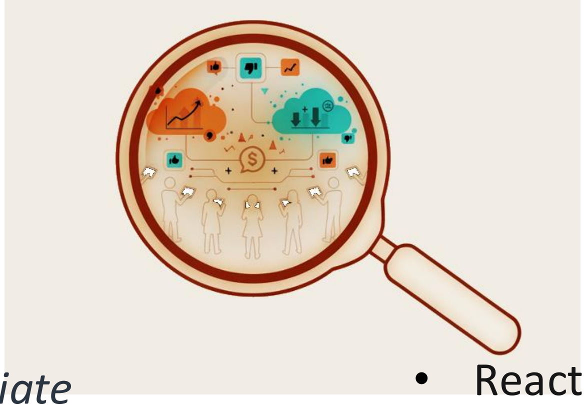
Method: comments on social media content, viewing social media as a public sphere open to "all"

How: mixed-methods approach: automated sentiment tools and manual thematic coding

RQ1: How do people react to a virtual commensal companion on social media?

RQ2: How do automated sentiment analysis tools compare to manual coding in capturing these reactions?

Social media as an early lens on public reception of emerging technologies



Opportunities

- Social media offers *immediate access* to public reactions
- Comments provide *authentic, unprompted* perspectives
- Large-scale data enables *trend detection* and *early signals* of acceptance/rejection

Challenges

- Reactions may be shaped by *meme culture*, irony, and generational styles
- Automated tools risk *misclassifying* sarcasm and stylized disapproval
- Mostly “active” Instagram users are just a subpopulation

Media content

https://www.instagram.com/reel/C900KFNOH5l/

Existing post on Instagram ”The Guy brought his virtual girlfriend out for sushi. . .”

- Large, diverse user base across generations
- Platform where meme culture and social commentary converge
- Public comments are rich in sarcasm, humor, and cultural framing

- Viral reach with thousands of views and hundreds of comments
- Clear focus on a virtual dining companion
- Balanced mix of supportive, critical, and playful reactions

Methodology

1 Dataset

- *n=719* Instagram comments (including replies & repeat users)
- multiple languages
- no demographics or user account data available

2 Automated Sentiment Analysis

- applied four widely used tools:
  - TextBlob, VADER, NRCLex, and a BERT-based transformer
- each tool assigned polarity or emotion labels to all comments
- emoji and GIF sentiment analysis

3 Manual Thematic Coding

- entire dataset hand-coded using a *qualitative thematic, **Grounded Theory*** approach
- final scheme: **25 categories** (e.g., approval/disapproval subtypes, etc.)

Results: automated sentiment analysis

- **TextBlob: assigns overall sentiment polarity (–1 to +1) and subjectivity (0 = objective, 1 = subjective)**
  (e.g., *“I'm actually sick and tired of this guy but hey that's his hustle”* - polarity: -0.56, subjectivity: 0.78
  “I don’t understand why but… that’s fine” - polarity: 0.42, subjectivity: 0.5)

- **VADER: returns ratios of negative, neutral, and positive tone plus an aggregated compound score**
  (e.g., “*I'm actually sick and tired of this guy but hey that's his hustle*” - {'neg': 0.272, 'neu': 0.728, 'pos': 0.0, 'compound': -0.4767}
  “I don’t understand why but… that’s fine” - {'neg': 0.0, 'neu': 0.795, 'pos': 0.205, 'compound': 0.2023}

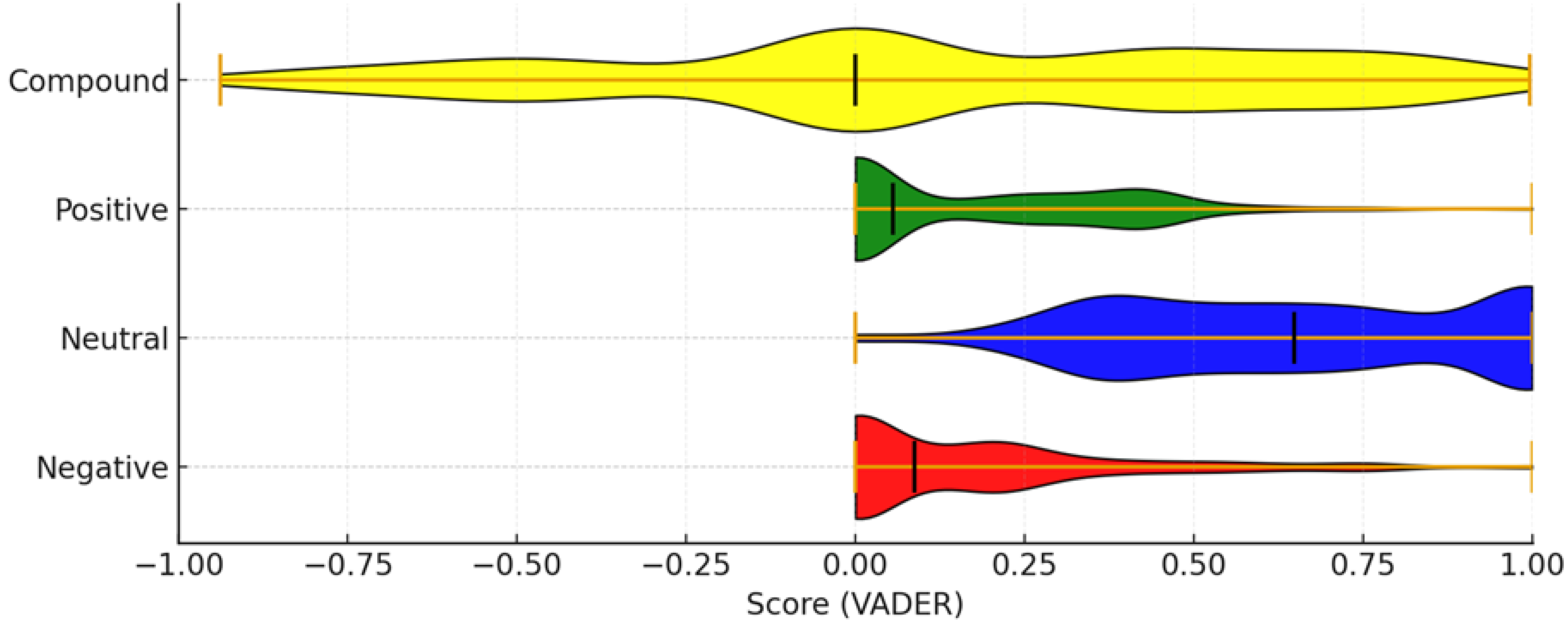
- **NRCLex: counts words linked to emotions (e.g., joy, fear, anger, trust)**
  (e.g., “*I'm actually sick and tired of this guy but hey that's his hustle*” - {'disgust': 1, 'negative': 2, 'sadness': 1})
  “I don’t understand why but… that’s fine” - {'positive': 1, 'trust': 1}

- **Transformer-based Emotion Models (BERT): predict probability distributions across multiple emotions**
  (e.g., “*I'm actually sick and tired of this guy but hey that's his hustle*” - {'sadness': 0.89, 'joy': 0.00, 'love': 0.00, 'anger': 0.06, 'fear': 0.03, 'surprise': 0.00})
  “I don’t understand why but… that’s fine” - {'sadness': 0.01, 'joy': 0.98, 'love': 0.00, 'anger': 0.00, 'fear': 0.00, 'surprise': 0.00}

Automated sentiment analysis

TextBlob – mean (std)	polarity (scale -1 to 1): **0.025** (0,297); subjectivity (0 to 1): **0.273** (0,357)
VADER - mean - (std) of the ratios across comments overall ratio based on compound scores	positive: **17,9** (22,0)%, neutral: **65,4** (27,4)%, negative: **16.7** (21,1)% positive: 49,3%, neutral: 27.9%, negative: 22.8%
NRCLex - percentage of words linked to affect-related keywords	positive (21,25%), negative (14,14%), trust (13,98%), joy (10,23%), anticipation (9,6%), sadness (7,57%), fear (7,03%), surprise (5,62%), disgust (5,16%)
Transformer-based Emotion Models (BERT) - mean (std dev) of the ratios across comments	joy: **32,8** %, anger: **29,4** %, sadness: **17,0** %, fear: **15,1** %, surprise: **0,03** %

Sentiment analysis: VADER example



Manual coding

- Coding followed a *Grounded Theory* approach: categories emerged inductively from the data
- Iterative process of reviewing, refining, and consolidating categories
- Final scheme: **25 categories**
- Each comment could be assigned to multiple categories (co-occurrence allowed)
- Manual coding revealed sarcasm, irony, and cultural nuance <u>not captured by automated tools</u>

Theme	Frequency
Approval – Bravery	24
Approval – Defensive	61
Approval – Jealousy	20
Approval – Live & Let Live	105
Approval – Sympathy	36
Disapproval – Bad for Society	113
Disapproval – Concern for Mental Health	89
Disapproval – Disgust	70
Disapproval – Judgment	411
Disapproval – Mocking	389
Disapproval – Pity	150
Focus on Social Constructs	74
Focus on bystander	19
Gendered Resentment	76
Lack of Understanding or Confusion	31
Objective Judgment	5
Pop Culture Reference	11
Privacy Concern	1
Relate to Self	43
Romantic Self-Projection	27
Suspected Spam	1
Thought it was VR	2
Thought it was a Real Person	5
Thought Post was Spam	5
Vague Curiosity or Interest	19

RQ 1: user reactions

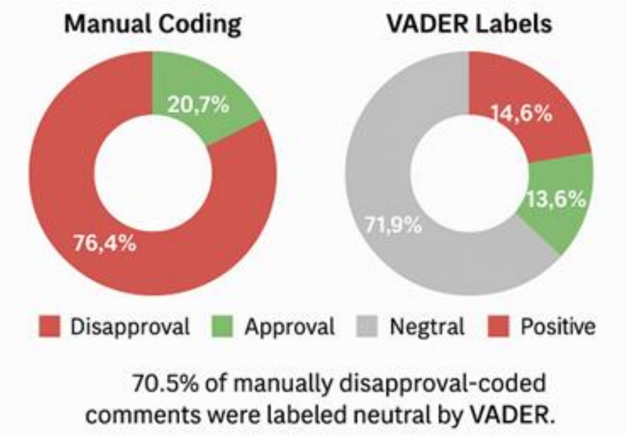
Disapproval dominated (~76%) of manually coded comments:

- most frequent: **Mocking, Judgment, Pity, Relational reflection**
- highlights interpretive layering: comments carried multiple meanings at once
- majority comments targeted the *user* (the guy), not the technology itself
  - negative personal judgments and quite frequent gendered resentments, e.g., “At least she won’t nag"
  - in line with our previous works: <u>fear of being judged</u> and <u>social stigma</u> can be an issue

People may be interested in using this technology, but they might not want others to know it.

RQ 2: text analysis of social media content

- Automatic tools systematically misclassify sarcastic, ironic, emoji-rich content as positive or neutral



Comment (shortened)	Manual	VADER	RoBERTa
"😄"	Mocking	Positive	Neutral
"@user maybe he doesn't want to deal with real girls and lose his peaceful life 😂"	Gendered Resent-ment	Neutral	Negative
😂😂😂😂😂😂😂😂😂😂😂	Mocking	Positive	Neutral
"@user😅 💀"	Mocking	Neutral	Neutral
"He is going to ask her to split the bill 😂"	Judgment + Mock-ing	Neutral	Neutral
"She paid with her virtual card 😂"	Mocking	Neutral	Neutral
"This is so cringe 😭"	Judgment	Negative	Negative
😭 🤦‍♀️	Judgment	Negative	Negative
"@user 😂😂😂"	Mocking	Positive	Neutral
"@user 😭😭"	Judgment	Negative	Neutral

- Emojis frequently used to signal mockery or judgment were misread as joyful or neutral by sentiment models

"Finally a girl who won't leave you 😭😭"

"He's braver than the troops 💀💀💀"

Conclusions and Future works

Conclusions:

- automated sentiment tools systematically missed sarcasm, irony, and layered meaning > manual coding might be still essential
- frequent negative personal judgments and gendered resentments
- training automated systems on manually coded data may provide a middle ground

Future Research:

- consider other social media (e.g., TikTok, LinkedIn, Reddit) becouse different community norms
- create own content in the same line
- manipulate the context of the same post (e.g., gender, the role of VR caracter)
- study social stigma in context of emerging technologies

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Crazy no! ? It's Time!

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Thank you for your attention!

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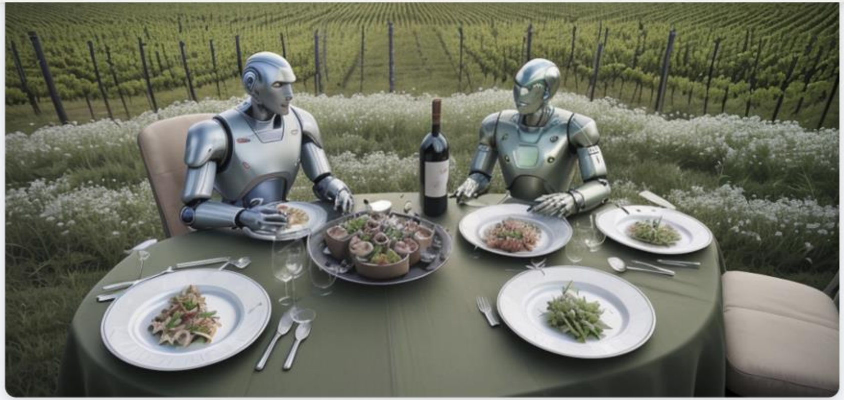

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