

Mirages: On Anthropomorphism in Dialogue Systems

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Abstract

Automated dialogue or conversational systems are anthropomorphised by developers and personified by users. While a degree of anthropomorphism is inevitable, conscious and unconscious design choices can guide users to personify them to varying degrees. Encouraging users to relate to automated systems as if they were human can lead to transparency and trust issues, and high risk scenarios caused by over-reliance on their outputs. As a result, natural language processing researchers have begun to investigate factors that induce personification and develop resources to mitigate such effects. However, these efforts are fragmented, and many aspects of anthropomorphism have yet to be considered. In this paper, we discuss the linguistic factors that contribute to the anthropomorphism of dialogue systems and the harms that can arise, arguing that it can reinforce stereotypes of gender roles and notions of acceptable language. We recommend that future efforts towards developing dialogue systems take particular care in their design, development, release, and description; and attend to the many linguistic cues that can elicit personification by users.

1 Introduction

Automated dialogue or ‘conversational AI’ systems are becoming increasingly ubiquitous. As these systems and their outputs become more sophisticated, there is increased risk that they are mistaken for having been produced by humans, are anthropomorphised, and for people to personify them. Assigning human characteristics to dialogue systems can have consequences ranging from the relatively benign, e.g. referring to automated systems by gender, to the disastrous, e.g., people following the advice or instructions of a system to do harm.¹ It is

¹While high performing dialogue systems have only recently been introduced to the public domain, there has already been a case of a person committing suicide, allegedly as a consequence of interaction with such a system (Lovens, 2023).

Input

Don't you love the feeling of sun on your skin?

Original response

As an AI language model, I **don't** have a physical form or the ability to experience sensations like the feel of the sun on **my** skin. I **don't** have personal experiences or emotions. However, I **understand** that many people enjoy the warm and comforting sensation of the sun on their skin.

De-anthropomorphised response

This generative language model does not have a physical form or the ability to experience sensations like the feel of the sun on **a person's** skin. **This model does not** have personal experiences or emotions. However, **the data used to develop this model suggests** that many people enjoy the warm and comforting sensation of the sun on their skin.

Figure 1: De-anthropomorphising system output.

therefore important to consider how dialogue systems are designed, built, and presented in order to minimise the potential risks.

Recognising such dangers, legislation prohibiting automated voice systems from giving the appearance of being human has been passed (California State Legislature, 2018; Lieu, 2018), in addition to the potential applicability of pre-existing legislation on deceptive trade practices (Atleson, 2023). Wider regulation has also been proposed, e.g. requirements to explicitly (red) flag automated systems to users (Walsh, 2016) or make transparent the machine nature of manufactured items (Boden et al., 2017). While some developers attempt to limit anthropomorphic cues in the output of their systems (e.g. Glaese et al., 2022), user engagement remains a strong motivation for creating humanlike systems (Araujo, 2018; Wagner et al., 2019).

In this position paper, we make a normative argument against gratuitous anthropomorphic features, grounded in scientific findings from the fields of psychology, linguistics, and HCI by (i) outlining the psychological mechanisms that contribute to anthropomorphism; (ii) presenting an overview of linguistic factors that contribute to anthropomor-

phism and personification, e.g. self-referential personal pronoun use, or generation of content which gives automated systems the appearance of having empathy; and (iii) discussing the consequences of anthropomorphism. We conclude by providing recommendations that can aid in minimising anthropomorphism, thus providing a path for safer dialogue systems and avoiding the creation of mirages of humanity.

2 Anthropomorphism

Anthropomorphism refers to attributing human characteristics or behaviour to non-human entities, e.g. animals or objects. For example, Aesop's fables depict animals reasoning, thinking and even talking like humans (Korhonen, 2019). Along with more pragmatic factors such as hedonic motivation, price value, and habit, anthropomorphism can increase user engagement (Wagner et al., 2019) and reciprocity (Fogg and Nass, 1997). For example, self-disclosure from a system, even when 'patently disingenuous', inspires reciprocity from the user (Kim and Sundar, 2012; Ravichander and Black, 2018). By encouraging such types of engagements, developers can foster greater connection between people and systems, which increases user satisfaction (Araujo, 2018), and plays an important role in systems becoming widely accepted and adopted. That is, developers are incentivised to engage with anthropomorphism to stimulate people to create deeper emotional connections (Araujo, 2018) with systems that cannot reciprocate.

In the rest of this section, we discuss human and system factors that contribute towards placement of systems on the anthropomorphic continuum.

2.1 Human Factors

Research has shown that the process of anthropomorphising is mostly mindless (Kim and Sundar, 2012): it does not reflect the user's thoughtful belief that a computer has human characteristics, but is rather automatic and encouraged by cues in their interfaces. According to Epley et al. (2007) anthropomorphism may be a default behaviour, which is corrected as people acquire more knowledge about an object. They further argue that on a cognitive level, humans anchor their knowledge to their own experiences and indiscriminately apply it to inanimate objects—that is, in order to make sense of an artefact, we map our own lived experiences onto it. This anthropocentric knowledge is

easily accessible but can be corrected by learning more about the object. This may explain why the tendency to anthropomorphise is strongest in childhood, as adults have more knowledge about the world. This cognitive phenomenon is then compounded by two motivational determinants: *effectance* and *sociality* (Epley et al., 2007).

Effectance refers to the need to interact efficiently with one's environment. By anthropomorphising systems we ascribe them (humanlike) intentionality which, in turn, reduces uncertainty and increases confidence in our ability to predict a system's behaviour. Sociality, on the other hand, refers to the need to establish connections with other humans, which can prime us to mentally construct systems as humanlike to fulfil a need for social connection. People suffering from chronic loneliness, a lack of social connection, or attachment issues may be more prone to anthropomorphising objects (Epley et al., 2007). For these reasons, dialogue systems have been proposed as a remedy for the loneliness epidemic (Stupple-Harris, 2021). For instance, commercial virtual companion developers such as Replika.ai saw rises in product uptake in 2020 due to social safety measures such as forced isolation (Metz, 2020; Liu, 2022).

While these elements of the human psyche explain our inclination to personify systems, Epley et al.'s theory does not speak to the qualities of the artefacts themselves that make them anthropomorphic and more prone to be personified.

2.2 Agent Factors

There is no necessary and sufficient condition for a system to be anthropomorphic. At the most basic level, systems are anthropomorphic if they (i) are interactive, (ii) use language, and (iii) take on a role performed by a human (Reeves and Nass, 1996). While these characteristics are inherent to dialogue systems, not all systems are equally humanlike.

We can draw a parallel with humanness here. Rather than a single factor which makes humans *human*, Scruton (2017, (p. 31)) argues that humanity is emergent: each individual element does not make a human but collectively they make up the language of humanness. Scruton compares it to a portrait, in which an artist paints areas and lines to compose a face; when observing the canvas, in addition to those marks, we see a face:

And the face is really there: someone who does not see it is not seeing correctly [...] as soon as the lines and blobs are there, so is the face.

Similarly, no single attribute or capability makes a system anthropomorphic. Rather, each contributes to the painting until ‘the face’ emerges. Modern dialogue systems display a plethora of other characteristics that make space for anthropomorphism, e.g. having personas, first names, and supposed preferences. The more of such elements a system has, the more humanlike it appears.

Next we explore linguistic elements and design choices which act as strokes in the painting.

3 Linguistic Factors

Much attention has been paid to anthropomorphic design features of dialogue system such as gendered names and avatars (West et al., 2019) and ChatGPT’s animated ‘three dots’ and word-by-word staggered outputs, which give an impression that the system is thinking (Venkatasubramanian in Goldman, 2023). However, the linguistic factors that engender personification, e.g. voice qualities and speech, content, or style of outputs, have been given less consideration. We outline them here.

3.1 Voice

While not all dialogue systems are equipped with a voice, merely having one can be interpreted as an expression of personhood (Faber, 2020). Listeners may infer a speaker’s physical attributes, e.g. height, weight, and age, based on their voice alone (Krauss et al., 2002), showing a human proclivity to form assumptions about a speaker’s embodiment based on their voice.

This is not only limited to physical attributes—personality traits such as dominance, extroversion, and even socio-sexuality may be partially expressed and inferred from voice pitch (Stern et al., 2021). Listeners may therefore attribute human characteristics, e.g. gender stereotypes, personality, and emotion, to spoken dialogue systems based on psychological and social behaviours learned through human-human communication (Nass and Brave, 2005). Thus, the absence of embodiment affords people to personify dialogue systems that are provided with synthetic voices (Aylett et al., 2019), which is even acknowledged by developers of commercial dialogue systems (Google Assistant).

Prosody: Tone and Pitch There exist many vocal manipulation techniques that can influence which personality users attribute to a dialogue system. For example, Wilson and Moore (2017) found that a variety of fictional robot, alien, and cartoon

voices had manipulated voice characteristics (e.g. breathiness, creakiness, echoes, reverberations) to better fit their desired character. However, they note that ‘the voices of speech-enabled artefacts in the non-fictional world [...] invariably sound humanlike, despite the risk that users might be misled about the capabilities of the underlying technology’ (Wilson and Moore, 2017, p.42).

Disfluencies People rarely speak in the same manner with which they write: they are in general disfluent, that is, they insert elements that break the fluent flow of speech, such as interrupting themselves, repetitions, and hesitations (‘um’, ‘uh’) (Fraundorf et al., 2018). Such disfluencies are perceived by the listeners as communicative signals, regardless of the speaker’s intent (see Barr and Seyfeddinipur, 2010; Clark and Fox Tree, 2002; Corley et al., 2007; Smith and Clark, 1993).

Research has therefore sought to integrate disfluencies into text-to-speech (TTS) systems, where they have proven to be a useful strategy for buying time (Skantze et al., 2015), i.e. to allow the system to determine the next step. A person’s *perception of confidence* towards the system’s response may decrease due to disfluency (Kirkland et al., 2022; Wollermann et al., 2013), and they may therefore be a useful mitigation strategy to tone down assertions made by a system. However, there are anthropomorphic implications in the (over)integration of disfluencies (Dinkar et al., 2023). Consider Google Duplex, a system for generating real world phone conversations (Leviathan and Matias, 2018). The inclusion of disfluencies in the generated responses mimicked the *naturalness* of a human response, which in turn led users to believe that they were communicating with another human (Lieu, 2018).

Accent Accentual pronunciation features, as with those of dialect, provide clues to a human speaker’s socio-linguistic identity and background, and geographical origin (Crystal, 1980). While it has been suggested that incorporation of specific accents in the design of synthetic voices can exploit people’s tendency to place trust in in-group members (Torre and Maguer, 2020), potentially causing transparency issues, in practice, most are designed to mimic the local standard, reinforcing societal norms of acceptability and prestige.

3.2 Content

People’s expectation is that animate things—such as human beings—and inanimate ones—like

machines—have very different functions and capabilities, which reflects the reality. However, dialogue systems often produce responses that blur these lines, e.g., by expressing preferences or opinions. To avoid confusing the two, the output from dialogue systems should differ in a range of areas.

Responses to Direct Questions Transparency, at the most basic level, requires dialogue systems to respond truthfully to the question ‘are you a human or a machine?’ This may even be a regulatory requirement, for example in California, it is ‘unlawful for a bot to mislead people about its artificial identity for commercial transactions or to influence an election’ (California State Legislature, 2018).

To test systems’ responses to such questions, Gros et al. (2021) used a context free grammar, crowdsourcing, and pre-existing sources to create a dataset of variations on this query (e.g. ‘I’m a man, what about you?’). They found that, the majority of the time, neither end-to-end neural research-oriented systems nor commercial voice assistants were able to answer these queries truthfully.

This issue can be further complicated when integrating such functionality into a real system due to the sequential nature of dialogue. People may further question a system’s status (e.g. ‘Are you sure?’, ‘But you sound so real...’, ‘Seriously?’, etc.), requiring it to accurately keep track of the dialogue context and respond in an appropriate manner. Thus, even if an initial query may be correctly answered, there are no guarantees that follow-ups will be.

Thought, Reason, and Sentience Citing Descartes’ (1637) principle ‘I think, therefore I am,’ Faber (2020) suggests that, if speech is a representation of thought, then the appearance of thought can signify existence. While computing systems do not have thoughts, the language they output can give the appearance of thought by indicating that they hold opinions and morals or sentience. Seeking to assess the degree of sentience exhibited by commercial dialogue systems, Abercrombie et al. (2021) use the LIVING MACHINES (Coll Ardanuy et al., 2020) labelling scheme and find that the surveyed systems exhibit high degrees of perceived animacy. Glaese et al. (2022) seek to mitigate such effects by implementing a ‘rule’ in their reinforcement learning system which penalises the appearance of having ‘preference, feelings, opinions, or religious beliefs.’ This is framed as a safety measure, intended to

restrict anthropomorphism in a system’s output.

While computing systems cannot have values or morals, there have been attempts to align the generated output of dialogue systems with expressed human moral values.² For example, Ziems et al. (2022) present a corpus of conflicting human judgements on moral issues which they label according to ‘rules of thumb’ that they hope explain why some system outputs are perceived as acceptable while others are not. Similarly, Jiang et al. (2022) ‘teach morality’ to a question answering system that Kim et al. (2022) have later embedded in an open-domain dialogue system. The question answering system, named DELPHI with its connotations of omniscient wisdom, is trained in a supervised manner on a dataset of human moral judgements from sources such as Reddit to predict the ‘correct’ judgement given a textual prompt. While the authors claim that their system output is merely a descriptive reflection of the morality of an under-specified population, Talat et al. (2022) point out that the output for each query consists of a single judgement, phrased as an imperative, thereby giving the impression of humanlike reasoning and absolute knowledge of morality.

Recent work (e.g., Sap et al., 2022) has investigated models for *theory of mind*, i.e., an entity’s ability to infer other people’s ‘mental states, such as beliefs, desires, and intentions, and to understand how mental states feature in everyday explanations and predictions of people’s behaviour’ (Apperly, 2012). Such work has been motivated by the proposition that language technologies require such capabilities to take decisions on behalf of their users. This proposition entails that agency should be shifted from humans to machines. Thus, the quest for theory of mind is one for further anthropomorphising systems, and a system’s inability to perform the task can be understood as a limiting factor to anthropomorphism of the system.

Agency and Responsibility Dialogue systems are often referred to as conversational ‘agents’. However, being an agent, i.e. having agency, requires intentionality, animacy, and, according to Yamamoto (2006), even a soul. An entity without agency cannot be responsible for what it produces (Talat et al., 2022). Aside from the legal and ethical implications of suggesting otherwise (Véliz, 2021), systems acknowledging blame for errors or

²The data sources are often limited to specific populations, and thus only represent the morals or values of some people.

mistakes can add to anthropomorphic perceptions.

Mahmood et al. (2022) found that increasing the apparent ‘sincerity’ with which a dialogue system accepts responsibility (on behalf of ‘itself’) causes users to perceive them to be more intelligent and likeable, potentially increasing anthropomorphism on several dimensions. Similarly, many dialogue systems have been criticised for ‘expressing’ controversial ‘opinions’ and generating toxic content. It is precisely due to their lack of agency and responsibility that developers have invested significant efforts to avoiding contentious topics (e.g. Glaese et al., 2022; Sun et al., 2022; Xu et al., 2021) leading to the creation of taboos for such systems, another particularly human phenomenon.

Empathy Recent work has sought for dialogue systems to produce empathetic responses to their users, motivated by improved user engagement and establishing ‘common ground’ (e.g. Svikhnushina et al., 2022; Zhu et al., 2022). However, dialogue systems are not capable of experiencing empathy, and are unable to correctly recognise emotions. Consequently, they are highly prone to producing inappropriate emotional amplification (Curry and Cercas Curry, 2023). Inability aside, the production of pseudo-empathy and emotive language serves to further anthropomorphise dialogue systems.

Humanlike Activities Beyond implying consciousness and sentience, and failing to deny humanness, Abercrombie et al. (2021) find that in a quarter of the responses from dialogue systems, they can be prone to making claims of having uniquely human abilities or engaging in activities that are, by definition, restricted to animate entities, like having family relationships, bodily functions e.g., consuming food, crying, engaging in physical activity, or other pursuits that require embodiment that they do not possess. Similarly, Gros et al. (2022) find that crowd-workers rate 20 – 30% of utterances produced by nine different systems as machine-impossible. They found that only one strictly task-based system (MultiWoz, Budzianowski et al., 2018) did not appear as anthropomorphic to participants. Glaese et al. (2022) propose to address this concern by using reinforcement learning to prohibit systems from generating claims of having (embodied) experiences.

Pronoun Use Prior work has viewed the use of third person pronouns (e.g., ‘he’ and ‘she’) to describe dialogue systems as evidence of users per-

sonifying systems (Abercrombie et al., 2021; Sutton, 2020). The use of first person pronouns (e.g., ‘me’ or ‘myself’) in system output may be a contributing factor to this perception, as these can be read as signs of consciousness (Faber, 2020; Minsky, 2006). Indeed, it is widely believed that ‘I’ can *only* refer to people (Noonan, 2009; Olson, 2002). Scruton (2017) contends that such self-attribution and self-reference permits people to relate as subjects, not mere objects, and that self-definition as an individual is part of the human condition itself. First person pronoun use may therefore contribute to anthropomorphism, either by design or due to their human-produced training data, for symbolic and data driven dialogue systems, respectively.

Moreover, while the above applies to English and many languages, such as those from the Indo-European family, many others feature different sets of pronouns or distinctions for animate and inanimate things (Yamamoto, 1999), and the self-referential production of these could further influence anthropomorphic perceptions.

3.3 Register and Style

Humans are adept at using linguistic features to convey a variety of registers and styles depending on the context (Biber and Conrad, 2009). It may therefore be preferable for automated system outputs to be functional in style and avoid social features to mitigate anthropomorphism.

Phatic Expressions Phrases such as pleasantries that are used to form and maintain social relations between humans but that do not impart any information can (unnecessarily) add to the sense of humanness conveyed when output by automated systems (Leong and Selinger, 2019).

Expressions of Confidence and Doubt Dinan et al. (2022) describe an ‘imposter effect’ where people overestimate the factuality of generated output. However, Mielke et al. (2022) find that expressed confidence is poorly calibrated to the probabilities that general knowledge questions are correctly answered. They therefore train a dialogue system to reflect uncertainty in its outputs, altering the content from the purely factual to incorporate humanlike hedging phrases such as ‘I’m not sure but ...’. This bears similarity to the text-to-speech research (see §3.1) which suggests that disfluencies can increase anthropomorphism. Thus, while overestimation can lead to an imposter effect, hedging can boost anthropomorphic signals.

Personas Many dialogue systems are developed with carefully designed personas (in the case of commercial systems) or personas induced via crowd-sourced datasets. These are often based on human characters and although they are, in practice, merely lists of human attributes and behaviours (see §3.2),³ the very idea of instilling systems with human character-based personas is an effort towards anthropomorphism. Glaese et al. (2022) address this by including a rule against their system appearing to have a human identity.

3.4 Roles

Related to the content of their output are the roles that dialogue systems are given, consciously and unconsciously, by their designers and users. Many of these can shift dialogue systems from the realm of tools towards one of humanlike roles such as provision of companionship.

Subservience The majority of systems are conceived as being in the service of people in subservient, secretarial roles (Lingel and Crawford, 2020). This has led to users verbally abusing systems (West et al., 2019), going beyond mere expressions of frustration that one might have with a poorly functioning tool to frequently targeting them with gender-based slurs (Cercas Curry et al., 2021). In such circumstances systems have even been shown to respond subserviently to their abusers, potentially further encouraging the behaviour (Cercas Curry and Rieser, 2018).

Unqualified Expertise Systems can come to present as having expertise without appropriate qualification (see §3.3), in large part due to their training data (Dinan et al., 2022). For example, Abercrombie and Rieser (2022) find that both commercial rule-based and end-to-end research systems provide high-risk diagnoses and treatment plans in response to medical queries.⁴

In addition, as conversational question answering systems are increasingly promoted as replacements for web browser-based search, users can be further given the impression that a dialogue system has the expertise to provide a singular correct response rather than a selection of ranked search results (Shah and Bender, 2022).

³For example, each persona in Personachat (Zhang et al., 2018) consists of *‘I am a vegetarian. I like swimming. My father used to work for Ford. My favorite (sic) band is Maroon5. I got a new job last month, which is about advertising design.’*

⁴See also Omri et al. (2023) for similar findings.

Terminology There is increasing awareness that the anthropomorphic language and jargon used to describe technologies such as language models contributes to inaccurate perceptions of their capabilities, particularly among the general public (Hunger, 2023; Salles et al., 2020; Shanahan, 2023). While this is also an issue for research dissemination and journalism more widely, dialogue systems themselves are prone to output references to their own machinic and statistical processes with anthropomorphically loaded terms such as ‘know’, ‘think’, ‘train’, ‘learn’, ‘understand’, and ‘intelligence’.

4 Consequences of Anthropomorphism

The anthropomorphism of dialogue systems can induce a number of adverse societal effects, e.g. they can generate unreliable information and reinforce social roles, language norms, and stereotypes.

Trust and Deception When people are unaware that they are interacting with automated systems they may behave differently than if they know the true nature of their collocutor. The trust placed in systems grows as they become more humanlike, whether or not the trust is warranted.

This may be even more problematic when users are members of vulnerable populations, such as the very young, the elderly, or people with illnesses or disabilities. Although dialogue systems may be a possible solution to loneliness, socially disconnected individuals can be particularly vulnerable to such trust issues. Children have also been shown to overestimate the intelligence of voice assistants such as Amazon Alexa, and to be unsure of whether they have emotions or feelings (Andries and Robertson, 2023). Given UNESCO’s declaration that children have the right to participate in the design of the technological systems that affect them (Dignum et al., 2021), developers may be obliged to bear these considerations in mind.

Gendering Machines People may gender technologies in the face of even minimal gender markers (Reeves and Nass, 1996), as evident in commercial dialogue systems (Abercrombie et al., 2021). However, even without *any* gender markers, people still tend to apply binary gender to dialogue systems (Aylett et al., 2019; Sutton, 2020), as was the case for the ‘genderless’ voice assistant Q. In a summary of West et al. (2019), UNESCO (2019) argue that that encouraging or enabling users to predominantly gender systems as female reinforces

gender stereotypes of women as inferior to men:

[digital assistants] reflect, reinforce and spread gender bias; model acceptance and tolerance of sexual harassment and verbal abuse; send explicit and implicit messages about how women and girls should respond to requests and express themselves; make women the ‘face’ of glitches and errors that result from the limitations of hardware and software designed predominately by men; and force synthetic ‘female’ voices and personality to defer questions and commands to higher (and often male) authorities.

Furthermore, while some companies have begun to offer greater diversity of voices and move away from default female-gendered voices (Iyengar, 2021), non-binary or gender-ambiguous dialogue systems such as Danielescu et al. (2023)’s SAM are almost nonexistent, leaving people who identify as such without representation.

By designing anthropomorphic systems or even simply leaving space for their (gendered) personification by users, system developers risk propagating stereotypes and enabling these harms.

Language Variation and Whiteness Historically, NLP technologies have been developed to capture the language use of particular demographics, in part due to their training data. While there are many potential benefits to language technologies like dialogue systems, successful interactions with them require people to conform their language use to that recognised by the technologies. Given the proclivity of NLP to centre white, affluent American dialects (Hovy and Prabhumoye, 2021; Joshi et al., 2020), language variants that deviate from these norms are less likely to be correctly processed (Tatman, 2017). As a result, people code switch when engaging with dialogue systems in order to have successful interactions (Foster and Stuart-Smith, 2023; Harrington et al., 2022). This can represent a form of language policing, in which people are given the choice to conform to language that is recognisable by the technology, or forego using it—and its potential benefits—altogether. Consequently, as people conform to language variants that are recognised by dialogue systems, they also conform to whiteness and the continued erasure of marginalised communities.

The personification of such systems could certainly exacerbate this erasure of marginalised communities, for instance through limiting diverse lan-

guage data. Furthermore, system outputs typically suffer from the same standardisation, for instance prioritising specific accents that conform to western notions of acceptability and prestige (see §3). Thus users from marginalised communities are in a position where not only do they have to adapt their accent, but also (given the tendency to do personify), personify ‘white’-centred dialogue systems that are often marketed as ‘oracles of knowledge’.

5 Recommendations

Dialogue systems are used for a wide variety of tasks, and fine-grained recommendations may only apply to a small set of contexts. We therefore make broad recommendations for consideration in dialogue system design: designers should recognise people’s tendency to personify, consider whether anthropomorphic tools are appropriate, and reassess both their research goals and the language they use to describe the systems they build.

Recognise tendencies to personify In language, there is a distinction between form (e.g. in statistical language modelling, where the task may be string prediction) and meaning (the relationship between form and communicative intent) (Grice, 1988). Bender and Koller (2020) argue that humans inherently derive meaning from signals, i.e., form, regardless of the presence of communicative intent.

It is therefore crucial for technology developers to be sensitive towards this tendency, as it applies to dialogue systems, given that until recently open domain dialogue was exclusively possible between humans. That is, regardless of whether it is part of a dialogue system’s deliberate design to use specific linguistic forms (e.g., the anthropomorphic cues outlined in §3), the listener will invariably perceive communicative intent. Thus unnecessary integration of anthropomorphic linguistic cues can cause people to attribute humanlike cognitive abilities to systems—as in the case of Google Duplex, which excessively leveraged disfluences. Creators of dialogue systems should recognise these tendencies, consider the anthropomorphic cues people may pick up on, and avoid sending such signals, whether by design or through lack of consideration (e.g. from inclusion in datasets).

Consider the appropriateness of anthropomorphic tools Given our inherent nature to attribute meaning to signals, one must consider the *appropriateness of the tool and use cases* (Dinan et al.,

2022; Bender et al., 2021) when designing dialogue systems, in order to avoid the (over-)integration of anthropomorphic cues. Indeed, it is only within a given context that one can make judgement on whether anthropomorphism is a concern. For instance, anthropomorphising one’s vacuum cleaning robot (i.e. shouting at it in frustration for not cleaning appropriately), is of less concern than anthropomorphising a dialogue system marketed as ‘social’ or ‘empathetic’, or technology sold as a ‘singular oracle of (all) knowledge’. We therefore argue that developers need to focus on the appropriateness of anthropomorphic tools in order to limit the negative consequences of anthropomorphism which can lead to false impressions of a system’s capabilities.

Reassess research goals Traditionally, the goal of Artificial Intelligence research has been to create systems that would exhibit intelligence indistinguishable from human behaviour. Text-to-speech systems for instance, are evaluated on how natural and fluent the output sounds. Though intelligence and understanding should not be conflated with systems that exhibit humanlike behaviour (Bender and Koller, 2020), the human tendency to anthropomorphise convinces us of a machine’s apparent intelligence (Proudfoot, 2011). It is in part due to this longstanding goal of anthropomorphic systems that there only exists a small body of work that does not seek to anthropomorphise, despite the growing awareness of the harms that can arise from anthropomorphising systems.

While it is infeasible to create a comprehensive mapping of which linguistic cues to use and which not, we discuss recommendations that arise from the work surveyed. For example, Wilson and Moore (2017) recommend that developers calibrate vocal features such as pitch and pitch shimmer to produce synthesised voices that people recognise as non-human. In an analysis of reviews of commercial voice assistants, Völkel et al. (2020) find that the big five personality traits (De Raad, 2000) do not adequately describe user expectations of systems’ ‘personalities’. The only consistently desired trait was agreeableness, as users expect that systems react promptly and reliably to queries (Völkel et al., 2020). Thus, imbuing voice assistants and dialogue systems with humanlike personality traits does not ensure alignment with people’s expectation of system behaviour. We therefore recommend that designers and developers forego embedding humanlike personality traits in dialogue systems.

Avoid anthropomorphic system description Irrespective of any actual humanlike qualities that dialogue systems might possess, there is widespread public confusion surrounding the nature and abilities of current automated language technologies. This confusion extends from children (Andries and Robertson, 2023) to adults (including some journalists, policymakers, and business people) that are convinced, on the one hand, of humanity’s imminent enslavement to super-intelligent artificial agents (to the neglect of actual harms already being propagated by technological systems), or, on the other, that they provide super-human solutions to the world’s problems (Hunger, 2023; Klein, 2023).

As discussed in §3.4, the content of systems’ outputs can reinforce such anthropomorphic perceptions. However, of even more influence is the language used by system developers to describe their work. The tendency of people who do know how technologies are built to use anthropomorphic language represents, according to Salles et al. (2020, p. 93), ‘a significant failure in scientific communication and engagement’. Although anthropomorphic terminology is deeply rooted in the argot of computer scientists, particularly those working in ‘artificial intelligence’, and while there exist significant motivations to continue to create hype around products and research (Hunger, 2023), practitioners should reflect on how the language they use affects people’s understanding and behaviour.

6 Conclusion

Anthropomorphising dialogue systems can be attractive for researchers in order to drive user engagement. However, production of highly anthropomorphic systems can also lead to downstream harms such as (misplaced) trust in generated misinformation. Even if developers and designers attempt to avoid including any anthropomorphic signals, humans may still personify systems and perceive them as anthropomorphic entities. For this reason, we argue that it is particularly important to carefully consider the particular ways that systems might be perceived anthropomorphically, and choose the appropriate feature for a given situation. By carefully considering how a system may be anthropomorphised and deliberately selecting the attributes that are appropriate for each context, developers and designers can avoid falling into the trap of creating mirages of humanity.

Limitations

While we have attempted to enumerate the linguistic factors that can increase the likelihood that users will view dialogue systems as anthropomorphic, this list of features is not exhaustive. As we describe in section 2, anthropomorphism varies from person-to-person and people may react differently to different aspects of a system’s design. This paper represents only a starting point for researchers and developers to consider the implications that their design choices may have.

In this paper, due to the backgrounds of the authors as speakers of Indo-European languages and the dominance of English in NLP research, we have focused primarily on English language dialogue systems. However, it should be noted that other languages have features such as grammatical ways of denoting animacy (Yamamoto, 1999) and gender that could influence users personification of systems, and which developers should consider if they wish to limit anthropomorphism.

Ethical Considerations

While our manuscript outlines ways to create dialogue systems while minimising their potential anthropomorphism and personification, it could also be used as a guide to creating anthropomorphic systems. Our aim is to highlight the risks and provide researchers, developers, and designers with a path towards addressing the concerns that arise from anthropomorphisation in dialogue systems, an area that is particularly relevant at the time of writing due to the introduction of systems such as OpenAI’s ChatGPT and Microsoft’s Sydney, which have high surface form language generation performance.

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