

# On Moral Manifestations in Large Language Models

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Since OpenAI released ChatGPT, researchers, policy-makers, and laypersons have raised concerns regarding its false and incorrect statements, which are furthermore expressed in an overly confident manner. We identify this flaw as part of its functionality and describe why large language models (LLMs), such as ChatGPT, should be understood as social agents manifesting morality. This manifestation happens as a consequence of human-like natural language capabilities, giving rise to humans interpreting the LLMs as potentially having moral intentions and abilities to act upon those intentions. We outline why appropriate communication between people and ChatGPT relies on moral manifestations by exemplifying ‘overly confident’ communication of knowledge. Moreover, we put forward future research directions of fully autonomous and semi-functional systems, such as ChatGPT, by calling attention to how engineers, developers, and designers can facilitate end-users sense-making of LLMs by increasing moral transparency.

Additional Key Words and Phrases: ChatGPT, large language model, social agent, moral, manifest, moral cognition, overconfident

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## 1 INTRODUCTION

Since the public release of ChatGPT and other large language models (LLMs), the media has been quick to point to its potential impact on various domains (e.g., student reports, scientific articles). Moreover, concerns have been raised regarding the generation of false or wrongful knowledge. For example, ChatGPT has generated fake scientific abstracts that were able to deceive scientists into believing these abstracts were written by their peers [2]. Despite its ability to produce text in a human-like style, the answers provided can be wrong or based on non-existing sources [12].

Nonetheless, LLMs, such as ChatGPT, communicates in human-like ways, causing humans to anthropomorphise the system [9]. This gives rise to new perceptions of the system, in which constructs traditionally used to describe humans are now applied to systems (e.g., the belief that the other entity has a sense of what is right or wrong). While anthropomorphism has been a popular topic within HCI and related fields, the moral dimensions of anthropomorphism are not well understood. Fiske et al., point out that human perception of interpersonal behaviour helps to determine other people’s intentions and their capacity to realise these intentions [4]. These intentions (and the capacity to realise them) have moral dimensions, meaning that intentions (and the capacity to realise them) can be perceived and categorised as right or wrong. Consequently, this may influence human sense-making in ways we do not yet understand. We

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53 suggest that this understanding is particularly relevant in people’s interactions with LLMs, given their human-like  
54 communicative abilities and the growing application of LLMs in sensitive settings such as mental health [11].

55 The use of highly human-like language (e.g., overconfident communication style) by autonomous systems influences  
56 end-user perceptions. Various researchers have raised concerns about ChatGPT’s overconfidence in its answers to user  
57 prompts. The style of these answers has been described by people using negatively loaded metaphorical language such  
58 as ‘your average tech-dude’ or ‘over-confident dudes with shallow subject matter knowledge but high skill in faking  
59 expertise’ [3, 8]. This illustrates that humans might perceive LLMs as overly-confident individuals, resonating with the  
60 quality of interaction and potentially influencing it negatively and giving rise to discontinuing the interaction (e.g.,  
61 conversational break-down [10]). Moreover, overconfident answers may influence interactions in other ways we cannot  
62 yet anticipate, consequently posing risks to humans engaging with LLMs available to the public across a variety of  
63 tasks (e.g., asking for advice or writing assistance). We highlight that possible consequences are not only ethical in  
64 nature but also pose moral concerns.  
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## 69 2 LARGE LANGUAGE MODELS AS MORAL MANIFESTORS

70 As outlined above, people tend to anthropomorphise systems (e.g., LLMs) displaying natural language capabilities.  
71 When people anthropomorphise these systems, it naturally follows that people use their sense-making abilities to  
72 understand their experiences, as they would in making sense of other people around them. Therefore, we mean that  
73 communicative autonomous systems, such as large language models, belong to the space of social agents, in which  
74 both humans and non-humans are included in terms of functionality. As a consequence, LLMs should be understood as  
75 moral manifestors, manifesting moral dimensions through natural language at the same level as humans:  
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80 “By way of analogy, consider the concept VEHICLE. At a mechanical level, vehicles are extremely  
81 variable and not at all distinct from other things. A motorcycle, for example, has more in common  
82 with a lawn mower than with a sailboat, and a sailboat has more in common with a kite than with a  
83 motorcycle. One might conclude from this that the concept VEHICLE is therefore meaningless, but that  
84 would be mistaken. VEHICLES are bound together, not at the mechanical level, but at the functional  
85 level. I believe that the same is true of morality” [6, p. 40]  
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89 As such, seeing LLMs as members of this shared space populated by social agents, we should anticipate that humans  
90 interacting with such communicative autonomous systems use the same cognitive functions as when making sense of  
91 other humans (relying on cognitive processes such as perception, reasoning, or information processing). Moreover, this  
92 implies that humans also have expectations, attitudes, or perspectives that influence how they make sense of systems  
93 in different contexts.  
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95 How the anthropomorphising of publicly available LLMs (e.g., perceived overconfidence in ChatGPT’s answers)  
96 affects user interaction is still unclear. Therefore, the moral dimensions of overly confident responses, particularly when  
97 they are false or inappropriate, may have a discernible impact on human sense-making processes (e.g., an individual  
98 may have reduced trust in a system that provides incorrect responses [13]). Without a doubt, this has implications for  
99 a number of stakeholders, including end-users, engineers, and designers. We are breaking new ground in that lines  
100 between human and AI written text are getting blurry. This is illustrated by OpenAI, which recently described its new  
101 AI classifier to detect AI-written text (text primarily generated by ChatGPT, also developed by OpenAI):  
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105 “Our classifier is not fully reliable. In our evaluations on a ‘challenge set’ of English texts, our classifier  
106 correctly identifies 26% of AI-written text (true positives) as ‘likely AI-written,’ while incorrectly labeling  
107 human-written text as AI-written 9% of the time (false positives).”  
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109 Together with other researchers, we highlight that this ‘breaking new ground’ needs to happen responsibly. The  
110 human-centred approach to computing aligns well with having the user in focus and is therefore a suitable approach  
111 to follow up on suggested implications. The HCI community should therefore seek to comprehend how LLMs shape,  
112 influence, or even harm their users through the use of fully autonomous and semi-functional communicative autonomous  
113 systems such as ChatGPT. To do so requires us to see ChatGPT and similar systems as social agents manifesting morality  
114 that can be designed and manipulated. More specifically, we suggest that moral manifestations should be understood  
115 through the psychological and cognitive processes surrounding morality [6]. This requires us to presume communicative  
116 autonomous systems as moral manifestors similar to how we pose humans as moral manifestors.  
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### 120 3 FUTURE RESEARCH DIRECTIONS

121 In general, deploying large language models into the wild results in a wild variety of conversational topics. By considering  
122 large language models as social agents manifesting morality, researchers can better assess their impact on end-user  
123 perceptions and provide concrete recommendations for designing these systems across various contexts. Future research  
124 must seek to align LLMs moral manifestations through social communication abilities with end-user expectations (e.g.,  
125 by avoiding overconfidence in its communication). Currently, LLMs manifest morality by providing (overconfident  
126 communication, potentially false or wrongful) answers we do not want in ways we do not like. We suggest that by  
127 understanding LLMs as moral manifestors and by introducing moral transparency, chances are increased of meeting  
128 end-user expectations.  
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130 More specifically, we call attention to the need to increase moral transparency (i.e., morally relevant transparency [7])  
131 of LLMs. Increasing moral transparency can partly be achieved by referencing the answers provided. Similarly to the  
132 argument put forward by Glaese et al., this allows users to assess the source of the answer and to form an opinion  
133 about its correctness [5]. It can be posited that this would potentially empower humans to retain decision-making  
134 authority. Furthermore, advances in computational fact-checking can provide tools to verify the truthfulness of LLM  
135 output. Journalists already use fact-checking to compare claims by public figures or social networks with reference  
136 corpus to verify the authenticity of information [1]. Computational fact-checking could be a valuable asset to assess a  
137 *priori* truthfulness of the answers provided by LLMs.  
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139 To understand the impact of overly confident answers provided by LLMs, as well as other manifestations of human  
140 behaviour that might arise in future LLMs, we need to understand better how people perceive the moral dimensions of  
141 LLMs and how this influences their perceptions of correctness and truthfulness. We call on the research community to  
142 further investigate the moral manifestations of LLMs and subsequently apply these insights to the design of future  
143 systems.  
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