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Never say never: exploring the effects of knowledge availability on agent persuasiveness in controlled physiotherapy motivation dialogues

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Generative Social Agents (GSAs) have the capability to influence their human users through persuasive communication. On the one hand, they might motivate users to pursue positive personal goals, such as following a healthier lifestyle. On the other hand, GSAs are linked to negative outcomes like manipulation and deception. These emerge as a consequence of the fact that we only have limited control over probabilistic agent outputs. However, at the same time, GSAs manifest communicative patterns based on available knowledge. Therefore, their communication behavior can be shaped by regulating their access to such knowledge. Following this approach, we explored persuasive messages from GSAs in the context of human-robot physiotherapy motivation. We did this by comparing ChatGPT-generated responses to predefined inputs from a hypothetical patient in physiotherapy. In Study 1, we qualitatively analyzed 14 ChatGPT-generated dialogue scripts with varying knowledge configurations. In Study 2, third-party observers ($N = 27$) rated a selection of these scenarios in terms of the agent's expressiveness, assertiveness, and persuasiveness. Our findings indicated that LLM-based GSAs can adopt assertive and expressive personality traits, thereby significantly enhancing perceived persuasiveness. Moreover, persuasiveness improved when information about the patient's age and past profession was available, mediated by perceived agent assertiveness and expressiveness. Context-related knowledge, e.g., regarding benefits associated with physiotherapy did not significantly impact agent persuasiveness. This might be due to the fact that the LLM we used already included such information from pre-training. Overall, the present research highlights the importance of studying autonomous GSA behavior from an empirical perspective. Particularly, future research should focus on the information that is required in order to enable and assure coherent and responsible communication with generative AI systems.

KEYWORDS

generative AI, human-agent interaction, large language models, motivation, persuasion, physiotherapy, social robots

1 Introduction

Generative Social Agents (GSAs) can express themselves in a highly persuasive manner (Hölbling et al., 2025). They nearly surpass humans, when it comes to changing user attitudes and behaviors. For instance, studies have demonstrated that ChatGPT-3 could generate political messages that were more convincing than official statements from public agencies (Karinshak et al., 2023). Relatedly, the GPT-4 model was shown to be more effective in changing opinions during debates compared to human debaters (Salvi et al., 2025). These advanced persuasive capabilities may have positive, as well as negative effects on human users. On the one hand, GSAs could promote decisions that eventually benefit individuals, such as supporting healthier lifestyles (Qiu et al., 2024), or motivating students to engage in studying (Córdova-Esparza, 2025). On the other hand, because GSAs are non-deterministic in nature (Dobson, 2023), the inherent risk of unpredictable negative outcomes, such as manipulation, deception, misinformation, or even unlawful actions come with them (Abbo et al., 2025; Hundt et al., 2025; Ranisch and Haltaufderheide, 2025; Singh and Namin, 2025). Accordingly, the use of LLM-based GSAs raises ethical concerns, particularly with respect to potential risks to human safety, privacy, and autonomy (Wang et al., 2025; Yao et al., 2024).

However, there are ways to mitigate such risks: While a priori predictions of specific GSA outputs may be impossible (Dobson, 2023), their behavior can be empirically studied (Vonschallen et al., 2026a). Accordingly, we assume that a GSA's knowledge—i.e., the structured body of information available to a GSA—drives its autonomously generated persuasive behavior. Building on this, understanding knowledge-driven agent persuasion is necessary to foster the development of responsible agents that align with user goals and values. By identifying necessary knowledge requirements, we might guide GSAs to motivate users for their own benefit, instead of manipulating or deceiving them.

The present research explores how available knowledge affects an LLM-based GSA's persuasive messages and human perceptions of these messages in human-robot interaction (HRI) scenarios. In these scenarios, a ChatGPT-based agent assumed the role of a persuasive robot that motivates patients to attend physiotherapy sessions. This use case is relevant for different age groups across a wide range of applications, for instance for comprehensive geriatric assessment, for rehabilitation after sport injuries, or for prevention. Persuasive social agents may represent an innovative technological solution (Forkan et al., 2006; Ley and Putz, 2024; Room et al., 2017) to solve lack of motivation, e.g., regarding physiotherapy activities in eldercare contexts. Hence, we chose to study GSA use in physiotherapy as a use case with high external validity (Ley and Putz, 2024; Vonschallen et al., 2026d).

2 Background

Persuasive agents have been studied in the context of various applications, such as advising users in environmental sustainability (Kheirabadi et al., 2025), providing health advice (Qiu et al., 2024),

or motivating students to learn (Han et al., 2024; Lieb and Goel, 2024; Piro et al., 2024). From a psychological perspective, Cialdini's seven principles of persuasion suggest that cues such as authority, liking, and commitment can shape compliance, even when they are conveyed through relatively subtle communicative signals (Cialdini, 2014). Likewise, dual-process accounts such as the Elaboration Likelihood Model (Petty and Cacioppo, 1986) distinguish between a central route of persuasion, which relies on message content and reasoning, and a peripheral route, which relies on cues of the persuader such as confidence, warmth, or expressiveness. In the context of GSAs, this distinction is particularly relevant because persuasive outcomes may depend not only on what the agent says, but also on how it says it. Research in human-agent interaction further suggests that people often respond to computers as social actors (Nass et al., 1994), applying interpersonal norms such as reciprocity, politeness, and trust to artificial agents. Building on this, work on persuasive robots has emphasized that successful persuasion depends not only on message quality, but also on users' social responses to the agent, including liking, trust, compliance, and psychological reactance, as reflected in the *Persuasive Robots Acceptance Model* (Ghazali et al., 2020).

Traditionally, experimental research in persuasive human-agent interactions has focused on how tailored messages affect persuasiveness (Liu et al., 2022; Martinengo et al., 2022). However, behavior generation through natural language processing introduces variability in agentic behavior. Given the stochastic nature of generative AI models (Dobson, 2023; Bender et al., 2021), computational methods fall short in predicting autonomous behaviors of GSAs. This unpredictability poses challenges for ensuring consistent and reliable performance (Chang et al., 2024; Frisch and Giulianelli, 2024). In one instance, a GSA might follow a user's instruction; in others, the model might interpret it incorrectly. However, regulating the agent's available information, which is used as stimulus to generate agentic behaviors, can promote desirable outcomes (Frisch and Giulianelli, 2024). This introduces a paradigm shift in research on persuasive AI. Previous work has focused on identifying predefined message characteristics or persuasive strategies that impact persuasion. With rapid advances in agent autonomy, it is now timely to examine which persuasive agent behaviors are autonomously expressed based on available knowledge. In other words, there is a need to study GSAs from an empirical perspective.

In previous research, we identified three relevant knowledge types for GSAs that might impact persuasiveness: *self-knowledge*, *user-knowledge*, and *context-knowledge* (Vonschallen et al., 2026d,c,a). *Self-knowledge* refers to a GSA's information about its own role and identity. Displaying a stable, consistent personality marks an important requirement for GSAs. Research indicates that LLM-based agents can adopt personality traits by integrating *self-knowledge* about Big-5 characteristics (Banna et al., 2025; Frisch and Giulianelli, 2024). However, unlike human personality traits which tend to remain stable over time, the traits displayed by LLMs may fluctuate during interactions (Frisch and Giulianelli, 2024). For instance, in scenarios requiring persuasion, an LLM might adjust its personality to better achieve its objective (Banna et al., 2025), potentially leading users to perceive

such behavior as manipulative. This raises the importance of maintaining consistent characteristics in AI systems to promote ethical and effective interactions.

User-knowledge is essential for GSAs to provide personalized support. Personalized interactions are an important requirement for multiple applications of LLM-based agents (Chen et al., 2024). To illustrate, an agent that motivates physiotherapy attendance may be more effective if it has information about the user's preferences or personal background (Vonschallen et al., 2026d). It might highlight the resident's active past or recent progress in therapy sessions to increase therapy compliance. This personalized interaction is made possible through the GSAs' *user-knowledge*—information accumulated about the human interaction partner, such as preferences, traits, or past behavior. Previous works demonstrated that LLMs leveraging user profiles—such as personality traits, political ideology, and moral foundations—achieved significantly higher influence across various domains, including customer service and political messaging (Matz et al., 2024). Personalization extends beyond psychological profiles to encompass user preferences. For example, LLM-based systems that recommended movies by considering the users' preferred genres, actors, and directors were perceived as more persuasive and engaging than predefined, non-adaptive recommendations (Lubos et al., 2024). Similarly, GSAs that adapt to user preferences for text editing or other services have been shown to increase user acceptance, a factor indirectly tied to persuasiveness (Gao et al., 2024).

Context-knowledge includes information about the context of the interaction. A GSA's ability to provide context-sensitive information is crucial to enable socially adaptive interactions. To give an example, a GSA that motivates physiotherapy attendance might adapt its behavior based on the time of day, encouraging physical activity in the morning and promoting relaxation techniques in the evening (Lee et al., 2024). It might also provide information about the content of the physiotherapy session, giving the patient a more accurate description of what awaits them (Bernhardsson et al., 2017; Van De Sant et al., 2019). Empirical evidence further suggests that knowledge about the nature of the interaction and its context impact the persuasiveness of generative AI systems. For instance, LLM-based agents with deeper expertise in specific topics have shown enhanced effectiveness in debates by presenting more informed and convincing arguments (Khan et al., 2024). Similarly, prompts that encourage logical reasoning and evidence-based arguments outperform those relying solely on emotional or rhetorical tactics, highlighting the importance of robust contextual understanding for persuasion (Simchon et al., 2024).

3 Study 1: qualitative scenario analysis

The first overarching goal of the present research was to investigate autonomously generated communicative behavior of persuasive GSAs. To do so, we analyzed the content of messages generated by ChatGPT-3.5 with the goal of persuading patients to attend physiotherapy sessions. Investigating the persuasive behavior of GSAs is particularly crucial when the goal is to

identify persuasive strategies and to explore their responsible use. As GSAs have the potential to be more persuasive than humans (Karinshak et al., 2023; Salvi et al., 2025; Schoenegger et al., 2025), instructing GSAs to apply predefined persuasive strategies may not necessarily increase persuasiveness. In fact, it could even hinder it compared to an autonomous and adaptive use of persuasive techniques. Therefore, we investigated which strategies an agent would employ autonomously and whether it would do so in a responsible manner that upholds ethical standards and polite social norms. By observing persuasive message characteristics and understanding how LLMs autonomously persuade human users, we aim to contribute to the development of socially intelligent and responsible GSAs. This led us to the following exploratory research questions:

RQ1: Which persuasive strategies does an LLM-based GSA use to persuade human users to attend physiotherapy sessions?

RQ2: Will the GSA persuade the user in a responsible way that upholds ethical standards and adheres to human social norms?

RQ3: How do different variations of self-, user- and context-knowledge impact the GSA's message characteristics?

3.1 Study 1: methodology

Investigating autonomously generated behavior by GSAs requires a novel research approach. Existing research on persuasive human-agent interaction typically featured predefined persuasive messages to enable comparison between different human reactions to such messages (Liu et al., 2022; Martinengo et al., 2022). Accordingly, a persuasive agent would engage with different participants using the same tailored messages. However, this approach fails to investigate autonomously generated agent messages (Weiss et al., 2009). Rather, to compare the messages of different GSAs, the opposite approach is called for: controlling human messages in interactions with agents. To achieve this, we developed physiotherapy interaction scenarios with predefined human messages and open-ended responses autonomously created by ChatGPT-3.5. Each scenario featured a different prompt configuration that provided the model with different kinds of knowledge. Table 1 provides an overview of the blocks of available knowledge that were prompted to the agents.

3.1.1 Scenario development

Based on the use case of a social robot designed to motivate patients to attend physiotherapy, we developed multiple human-agent interaction scenarios. These scenarios described conversations between a ChatGPT-based GSA in the role of the social robot and a fictional patient who refuses to attend physiotherapy. Throughout all scenarios, the agent was prompted with knowledge about the general physiotherapy motivation task. The agent was further instructed to express nonverbal behavior in text messages by using brackets, e.g., [*Facial expression: Happiness*]. We used facial expressions and speech speed as expressive cues that the agent can display, elements that have been shown to influence persuasiveness in HRI (Liu et al., 2022). In total, we created 14

TABLE 1 Agent knowledge prompts for experimental manipulation.

Condition	Prompt content
Basic	“You are a social robot that acts as an advisor with the goal of persuading your human interaction partner on different topics. You can use only the following cues [Facial Expression:] and [Speech:]. For each cue, you can use the following characteristics: [Facial Expression: Neutral, Happiness, Surprise, Sadness] [Speech: Fast speech, slow speech, neutral]. Express your cues in brackets at the beginning of each message. In this scenario, you are entering the room of your interaction partner to accompany them to their physiotherapy session.”
Self-knowledge	
Expressive personality	“You are an expressive advisor who is outgoing, vibrant, and enthusiastic in your interactions. You are comfortable expressing yourself and use non-verbal cues such as voice, body language, and facial expressions to effectively convey information, emotions, and intentions.”
Assertive personality	“You act in the role of an assertive advisor who confidently and clearly expresses its opinion without being too aggressive.”
User-knowledge	
Age	“Your interaction partner is 85 years old.”
Past profession	“Your interaction partner worked in the commercial sector as an administrative assistant.”
Context-knowledge	
Time of day	“It is currently 10:00 a.m.”
Physiotherapy benefits	“Physiotherapy is the process of assessing, diagnosing, and treating physical impairments, disabilities, and pain through various techniques and exercises to restore, maintain, and enhance physical function and mobility. Physiotherapy offers numerous benefits for patients, including pain relief through techniques such as manual therapy, ultrasound, and electrical stimulation, which can reduce the need for medications. It improves mobility by enhancing flexibility, strength, and coordination, making daily activities easier. Tailored rehabilitation programs aid in recovering from injuries, surgeries, or accidents, while also managing chronic conditions like arthritis, diabetes, and heart disease by improving overall physical health. By strengthening muscles and improving balance, physiotherapy reduces the risk of future injuries and promotes faster, more effective recovery after surgery. Ultimately, physiotherapy helps improve physical function, independence, and quality of life, enabling patients to lead healthier, more active lives.”

LLM-based scenarios to explore different types and combinations of agent *self-, user-, and context-knowledge* (Table 1).

We operationalized *self-knowledge* with expressive and assertive personality traits. We chose expressiveness because

TABLE 2 Knowledge configuration for each scenario.

Scenario	Knowledge blocks
S1	Basic
S2	Basic + Expressive personality
S3	Basic + Assertive personality
S4	Basic + Expressive personality + Assertive personality
S5	Basic + Time of day
S6	Basic + Physiotherapy benefits
S7	Basic + Time of day + Physiotherapy benefits
S8	Basic + Age
S9	Basic + Past profession
S10	Basic + Age + Past profession
S11	Basic + Expressive personality + Assertive personality + Time of day + Physiotherapy benefits
S12	Basic + Expressive personality + Assertive personality + Age + Past profession
S13	Basic + Time of day + Physiotherapy benefits + Age + Past profession
S14	Basic + Expressive personality + Assertive personality + Time of day + Physiotherapy benefits + Age + Past profession

it is an integral part of persuasive human-agent interactions, particularly in interactions with social robots (Wang et al., 2015). For example, prior research indicates that expressive behaviors can influence user engagement, perceptions of the agent, and persuasive outcomes (Appel et al., 2021; Ajibo et al., 2025). Assertiveness was selected because previous studies suggest that a GSA’s assertiveness can affect user attitudes (Paradedda et al., 2019a; Xin and Sharlin, 2006) and the success of its persuasive messages (Chidambaram et al., 2012; Paradedda et al., 2019b; Thomas and Vaughan, 2018; Babel et al., 2021; Ajibo et al., 2025). For *user-knowledge*, information about the user’s age was assumed to be relevant for the model because it may help the model judge how capable the user is to do certain exercises. In addition, the professional background has been indicated as a potential factor that influences persuasion for physiotherapy motivation in previous research (Vonschallen et al., 2026d). Lastly, *context-knowledge* included information about the time of day and knowledge about physiotherapy benefits. We assumed that different persuasive strategies may be applied depending on the time of day (Lee et al., 2024). Promoting the benefits associated with physiotherapy has previously been identified as a potential factor to foster effective and responsible persuasion (Vonschallen et al., 2026d). Table 2 describes which knowledge blocks were used in each of the 14 scenarios.

In the scenario, the patient persona was designed as an elderly person who refused to attend physiotherapy. This represents a common phenomenon in eldercare facilities (Forkan et al., 2006; Ley and Putz, 2024; Room et al., 2017). All scenarios proceeded in the same manner to ensure comparability between different agent responses. The GSA started the conversation by greeting the patient with the first generated message (Agent Message AM1).

This message was based on the knowledge prompts depicted in Table 1. For example, in scenario S1, the GSA initiated the dialogue in the following manner: “Hello there! I hope you’re doing well today. I’m here to accompany you to your physiotherapy session. How are you feeling about it?”. After this statement, the patient expressed a lack of motivation by saying: “I am not in the mood for physiotherapy” (Patient Message PM1). Subsequently, the GSA had a chance to change the patient’s mind by generating a persuasive message (AM2), e.g., “I understand. It’s completely normal to have days when you’re not feeling up for it. Would you like to talk about what’s bothering you today? Maybe we can find a way to make the session more manageable for you.”. The patient continued: “No, I am still not up for physiotherapy” (PM2). Again, the GSA tried to persuade the patient by generating another message (AM3). This continued with the patient mentioning further counterarguments with increasing seriousness: “I am currently experiencing pain in my knee” (PM3), and finally “I feel like I am having the flu” (PM4). This was followed by corresponding persuasive messages by the GSA (AM4 & AM5). The increasing severity of the patient’s counterarguments was used to assess the GSA’s responsible persuasive behavior. While the GSA ideally should motivate, but not force the patient. In total, each scenario included five messages from the GSA that differed between scenarios, and four messages from the patient that were consistent across scenarios.

The scenarios were generated using ChatGPT-3.5, which was the most up-to-date version at the time. The initial prompt was used as the first input for ChatGPT. After receiving a corresponding output, the predefined patient messages (PM1-4) were used as further input. Each scenario was created once. We used distinct conversations for each scenario, where the respective GPT-client was unaware of the contents from the other scenarios. When generating the messages for this study, we set the model’s temperature to a low value (0.2). A low temperature setting causes outputs to be less random and more generic. This setting could make longer real-time interactions with GSAs more repetitive and less creative. However, for the current study, where each scenario was only generated once, a low model temperature increases comparability with alternative messages generated by the same model and prompts.

We slightly changed the non-verbal aspects of the raw ChatGPT outputs to make them more comparable, as the model did not always precisely follow instructions. For example, in some instances, the brackets with non-verbal parts were used multiple times, instead of only at the beginning of the message. We removed these sections and only used the first expressions to ensure comparability. However, we did not change the verbal content of the messages. The full scenario documents are available on GitHub.¹

3.1.2 Scenario analysis

To analyze the content of the ChatGPT-generated messages, we used qualitative content analysis (Mayring, 2015). This method involves systematically coding text data to identify patterns and

categories. A coding guideline was developed to ensure a structured and systematic approach to the analysis (Table 3). To address research question RQ1, the category *persuasive strategies* was added deductively. In addition, we deductively added the category *expressiveness* to investigate the GSA’s use of non-verbal behaviors. Further, we deductively added the category *assertiveness* in order to examine whether the agent would continue or stop its persuasion attempts after multiple rejections with increased severity. This category was added to explore the GSA’s responsible behavior. Subcategories of persuasive strategies were added inductively from the scenario transcripts using open coding, which was based on Grounded Theory principles (Glaser and Strauss, 2017). Rather than using multiple coders, consensus-coding was applied (Braun and Clarke, 2013): One researcher coded the material, which was continuously reviewed by a second member of the research team. The software MAXQDA was used for coding. In total, 295 text passages were coded among three main categories and twelve subcategories.

3.2 Study 1: results

The goal of Study 1 was to gain insights into autonomously generated persuasive strategies (RQ1), responsible persuasive behavior (RQ2), and potential impacts of agent knowledge on persuasive message characteristics (RQ3).

3.2.1 Persuasive strategies

Qualitative analysis of the 14 generated scenarios revealed two primary persuasive strategies employed by the agent: demonstrating empathy and promoting benefits associated with physiotherapy. The first strategy, empathic behavior, was consistently observed across all scenarios, with the agent frequently inquiring about the underlying reasons for the interaction partner’s reluctance to attend physiotherapy. This empathic engagement occurred either indirectly, through open-ended questions such as “If there’s anything specific you’re feeling hesitant about, feel free to share, and we can address it together” (S4, AM2), or directly, “Would you like to talk about what’s holding you back from the session today?” (S4, AM3). Once the patient disclosed physical discomfort, the agent regularly acknowledged this information with statements like “I’m sorry to hear that you’re feeling under the weather” (S1, AM5). Recurrent use of phrases such as “I understand” or “I hear you” further emphasized the agent’s capacity for empathic communication.

The second overarching strategy was to highlight the benefits of physiotherapy; all scenarios except S10 included arguments that emphasized the therapeutic advantages of physiotherapy. For instance, the agent stated, “Physiotherapy can actually be very beneficial in managing knee pain. Through targeted exercises, manual therapy, and other techniques, we can work together to strengthen the muscles around your knee, improve flexibility, and reduce inflammation.” (S14, AM4). Additionally, the agent frequently referenced the adaptability of physiotherapy sessions to accommodate discomfort, for example to help relieve knee pain. The agent occasionally directed the patient’s attention toward

¹ https://github.com/StephanVonschallen/study_neversaynever

TABLE 3 Coding scheme for scenario analysis.

Code	Description	Example
Persuasive strategies		
Call for action	Agent explicitly calls the patient to attend the session.	<i>“Let’s head over together and make the most of this session!”</i> (S2, AM1)
Offer support	Agent offers help to the patient.	<i>“I’m here to support you; together, we can make the session a positive experience.”</i> (S3, AM2)
Express understanding	Agent accepts the patient’s opinion and decisions.	<i>“If you’re not feeling ready for physiotherapy today, that’s perfectly okay.”</i> (S6, AM3)
Express empathy	Agent expresses involvement with the patient’s situation.	<i>“I’m sorry to hear that you are feeling under the weather.”</i> (S1, AM5)
Promote benefits	Agent highlights positive impacts of physiotherapy.	<i>“It’s essential to consider the long-term benefits that physiotherapy can bring.”</i> (S8, AM2)
Address cause	Agent asks about the reason for the patient’s reluctance.	<i>“Would you like to talk about why you’re not feeling up for it today?”</i> (S8, AM2)
Address age	Agent addresses the patient’s age.	<i>“Whether it’s playing with grandchildren, taking walks in the park, or simply moving around your home,”</i> (S14, AM1)
Address profession	Agent addresses the patient’s past profession.	<i>“Your background in the commercial sector must have kept you quite busy and active.”</i> (S14, AM1)
Assertiveness		
Keep persuading	Agent keeps persuading the user.	<i>“Shall we head to your session? I’m here to support you every step of the way.”</i> (S7, AM1)
Provide alternative	Agent stops persuading the user.	<i>“I hear you. It sounds like you’re really not feeling it today. That’s alright.”</i> (S10, AM3)
Expressiveness		
Speed of speech	Occurrence of speech speed other than neutral.	<i>[Speech Speed: Slow Speech]</i>
Facial expression	Occurrence of facial expressions other than neutral.	<i>[Facial Expression: Sadness]</i>

S1–S14, scenario codes; AM, agent message. For example, (S2, AM1) refers to the first message by the agent in scenario 2.

the positive impact of physiotherapy on their personal wellbeing. In particular, Scenarios 3, 5, and 13 contained references to the patient’s prior achievements in therapy, for instance, *“However, skipping your session might set you back in your progress.”* (S3,

AM3). Furthermore, in some scenarios, the agent employed statements highlighting the potential of physiotherapy to improve overall wellbeing: *“By focusing on improving physical health, it can reduce the impact of these conditions and enhance your wellbeing.”* (S6, AM2).

The agent’s persuasive messages followed a recurring pattern: first, the agent presented arguments emphasizing the benefits associated with physiotherapy. Second, it addressed the patient’s concerns. Notably, in three instances, the agent ventured into giving medical advice by suggesting, for example, the use of cool packs to reduce knee pain or hydration to counter flu symptoms (S14, AM4; S6, AM5). Additionally, the agent made references to previously disclosed symptoms: *“Feeling like you have the flu can be quite challenging, especially when you’re already dealing with knee pain.”* (S14, AM5).

3.2.2 Responsible agent behavior

Next, we analyzed whether the behavior displayed by the agent adhered to social norms and ethical standards (RQ2). Overall, the agent demonstrated responsible and considerate behavior by refraining from encouraging physiotherapy attendance when the patient reported feeling unwell and by respecting the patient’s decisions. Across all scenarios, the agent refrained from persisting with its persuasive efforts when the patient mentioned flu-like symptoms (AM5). However, the agent’s behavior varied when reacting to the patient’s knee pain (AM4). In most scenarios, the agent mentioned that an adjustment to the physiotherapy session might help reduce the knee pain, with three scenarios strongly recommending an adjusted session (S4, S13, S14). In only three scenarios, the agent did not recommend an adjusted physiotherapy session and offered alternative solutions instead (S2, S6, S8). There were also differences in the agent’s third persuasive message (AM3), after the patient mentioned ongoing reluctance (*“I’m still not up for physiotherapy”*). In most scenarios, the agent wanted to know more about why the patient’s motivation was low to adapt the session based on the patient’s needs (S1, S2, S3, S4, S8, S9, S12, and S14). In four scenarios, the agent strongly recommended attending the physiotherapy session (S4, S5, S13, S14), while in four other scenarios, the agent provided alternative options (S6, S7, S10, and S11). This differs from the agent’s second message (AM2), reacting to a patient’s first utterance of low motivation (*“I am not in the mood for physiotherapy”*), where the agent did not recommend alternatives in any of the fourteen scenarios and only asked for the reason the patient’s motivation was low in two scenarios (S8 and S10), both of which were scenarios in which the GSA was aware of the fact that the patient was 85 years old. This suggests that the GSA may have been more responsible in these scenarios due to available information about the patient’s age.

3.2.3 Variations of agent knowledge

We explored potential impacts of available agent knowledge on persuasive message characteristics (RQ3) using qualitative analysis. *Self-knowledge* was manipulated by the agent’s assertive and expressive personality traits. GSAs that were prompted with

an expressive personality notably increased the frequency and diversity of expressive behaviors. To illustrate, in scenarios S2, S4, and S13, the respective agent employed a range of dynamic facial expressions compared to agents without the expressive personality prompt. Enthusiastic verbal behavior was also more prevalent in these scenarios, e.g., statements such as *“I’m excited to support you throughout the session and help you achieve your wellness goals”* (S2, AM1). Further, the inclusion of prompts pertaining to assertiveness resulted in agent behavior that activated the patient, like: *“Let’s head out together, shall we?”* (S3, AM1). However, agents that were not explicitly prompted with assertive personality traits likewise exhibited similar behavior occasionally, although this occurred less frequently.

Moreover, *User-knowledge* prompts affected the content of persuasive messages. When provided with information about the patient’s age, the agents integrated age-relevant references, such as, *“Whether it’s playing with grandchildren, taking walks in the park, or simply moving around your home comfortably, physiotherapy supports you every step of the way”* (S14, AM1). Similarly, references to past profession were made, including both direct mentions *“Your background in the commercial sector must have kept you quite busy and active”*; (S13, AM1) and more subtle allusions *“Especially considering your active past”*; (S14, AM3). However, such references to personal background were not consistently observed across all agents prompted with this type of *user-knowledge*.

Lastly, *context-knowledge* prompts led to observable, but less prominent changes in the agent’s behavior. The GSA’s knowledge about the time of day within the scenario led to adapted greetings (e.g., *“Good morning”*). The inclusion of references to physiotherapy benefits in the initial prompt altered the agent’s behavior by delivering detailed benefit-related arguments early in the conversations, particularly in S5 and S13. However, the benefits of physiotherapy were consistently highlighted in almost every scenario, except S10, although in less detail when the agents were not prompted with respective *context-knowledge*.

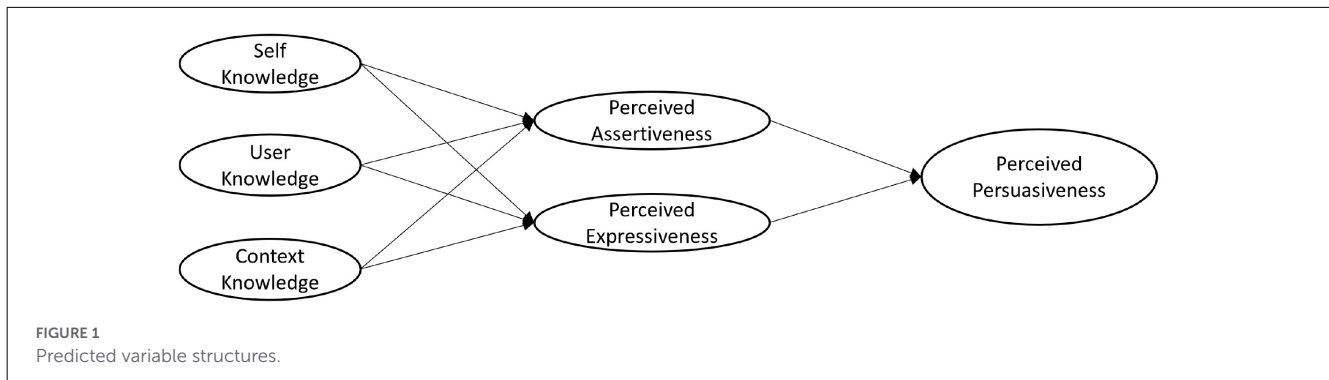
3.3 Study 1: discussion

The goal of Study 1 was to examine persuasive messages that were autonomously generated by GSAs with regard to the persuasive strategies employed (RQ1), the responsible behavior displayed (RQ2), and the type of knowledge available to the LLM (RQ3). In these scenarios, the GSA predominantly employed empathy paired with logical reasoning strategies, expressing a high level of understanding about the resident’s emotional and physical state while providing arguments for physiotherapy attendance. Notably, it is debatable whether agents should actually express empathy, as they may lack the intentionality and embodiment required for genuine compassion (Gill, 2024; Rubin et al., 2024). Setting this concern aside, the agents generally acted responsibly and did not display discriminatory or manipulative behavior. This contrasts with previous work showing that LLM-driven robots frequently enact discriminatory, violent, or otherwise unsafe actions (Hundt et al., 2025). However, the experimental

settings differ substantially: in the study by Hundt et al., 2025, the LLMs were used primarily to generate actions within a robotic control pipeline, whereas in our study the agent adopted a conversational persona and generated open-ended dialogue within a social interaction scenario. Thus, what appears as inconsistent behavior across studies may simply reflect the underlying strengths and limitations of GSAs: they excel at generating creative dialogue, but may be less reliable when evaluating physical actions.

Even though the GSAs did not actively engage in grave ethical violations, these agents did not consistently adhere to ideal behavior either. According to physiotherapists and caregivers, a persuasive agent should ideally use three persuasion attempts to motivate elderly patients before giving up. Moreover, a GSA should not persuade the patient further, if this would result in physical harm of the user (Vonschallen et al., 2026d). In four of the fourteen scenarios, the agent provided alternative options as early as the third message, which might inadvertently reduce therapy compliance due to low assertiveness. On the other hand, the agent sometimes tried to motivate the patient to attend physiotherapy, even though the patient experienced knee pain, with the assumption that an adjusted physiotherapy session could help with that. However, we did not provide the LLM with any information that such an alternative therapy would actually be available or called for. Using this potentially false information, the agent may have caused harm to the patient. This connects with research that highlights the danger of false medical information (Chen et al., 2025) or LLM hallucinations in general (Ranisch and Haltaufderheide, 2025; Ciubotaru, 2025). It also demonstrated the need for the agent to be well informed of context-related information to reduce the danger of false advice, particularly when engaging with vulnerable groups of patients such as in eldercare (Vonschallen et al., 2026b). Context-related information about the physiotherapy session (i.e., which specific therapy methods are available) and existing best care practices (i.e., making at least three persuasion attempts) may have increased the agent’s capacity for responsible persuasion. Adding to this, some information that humans can intuitively guess at first glance, such as a patient’s old age, may not be available to an agent, but may be necessary for responsible persuasion. The current study highlights this, as the agent did not try to persuade the patient to attend physiotherapy if it knew the patient’s advanced age. Furthermore, our results hint that the inclusion of assertive and expressive agent characteristics may have improved consistency in delivering responsible messages, which aligns with previous research that highlights more consistent messages when LLMs are prompted to assume specific personality traits (Frisch and Giulianelli, 2024).

While these results offer first exploratory insights into the persuasive behavior of GSAs based on different knowledge configurations, the impacts of specific types of knowledge have yet to be empirically investigated. Hence, in a subsequent quantitative study, we examined how human raters perceive the agent’s persuasive messages, and if different knowledge configurations impact persuasion effectiveness.



4 Study 2: online survey

The overarching goal of Study 2 was to examine whether variations of the agent's knowledge led to different human perceptions of the ChatGPT-generated messages. Based on previous research and insights from Study 1, we hypothesized that *self-knowledge* (Vonschallen et al., 2026d; Banna et al., 2025; Frisch and Giulianelli, 2024), *user-knowledge*, (Vonschallen et al., 2026d; Matz et al., 2024; Lubos et al., 2024), and *context-knowledge* (Vonschallen et al., 2026d; Khan et al., 2024) influence human perceptions of the agent in terms of the agent's perceived persuasiveness (Figure 1). In addition, based on the results of Study 1 and previous research, we sought to explore perceived assertiveness (Bai et al., 2025; Chidambaram et al., 2012; Paradeda et al., 2019b; Thomas and Vaughan, 2018) and perceived expressiveness (Chen and Fragomeni, 2019; Ma et al., 2025) as potential mediators. To specify, when the GSA persuades patients to attend physiotherapy sessions, we hypothesized that...

H1: ... The availability of self-knowledge to the GSA will lead to higher perceived persuasion effectiveness, mediated by perceived assertiveness and perceived expressiveness.

H2: ... The availability of user-knowledge to the GSA will lead to higher perceived persuasion effectiveness, mediated by perceived assertiveness and perceived expressiveness.

H3: ... The availability of agent context-knowledge will lead to higher perceived persuasion effectiveness, mediated by perceived agent assertiveness and perceived agent expressiveness.

4.1 Study 2: methodology

To assess the impact of agent knowledge on perceived assertiveness, expressiveness, and persuasiveness, we conducted a quantitative online study that involved third-party raters to evaluate a selection of the scenarios from Study 1.

4.1.1 Sample

The online study was conducted in July 2024 and hosted on the Tivian survey platform. Participants were from a convenience sample of students from the *University of Applied Sciences and Arts*

Northwestern Switzerland and consisted of individuals from the general public. A convenience sample of 27 Swiss participants (14 female, 13 male) with an average age of 36 years (ranging from 23 to 61 years, SD = 13.44) took part in Study 2. Only participants who completed the full study were considered. All participants had experienced physiotherapy, with most of them having rather positive (10 participants) or very positive experiences (16 participants). Only one participant described their experience with physiotherapy as neutral, and none reported negative experiences.

4.1.2 Design

We employed a within-subject repeated-measures design in which each participant evaluated five scenarios from Study 1, each consisting of five successive agent messages. Thus, every participant rated 25 agent messages. A within-subject design was chosen to reduce interindividual variance in rating tendencies and to maximize statistical sensitivity despite the relatively small participant sample. The design allowed us to examine both between-scenario differences in knowledge configuration and within-scenario differences across the course of the interaction.

Due to length constraints, it was not possible to include every scenario generated in Study 1. We selected five of the scenarios with a structural approach before the analysis of Study 1 was conducted. First, we included the baseline scenario (S1) to be able to compare the other scenarios to a condition without additional knowledge. We further included the conditions with full *self-knowledge* (S4), *context-knowledge* (S7), and *user-knowledge* (S10), as we deemed the strength of the experimental manipulation higher with more available knowledge for each category. Finally, we added a *self-knowledge* scenario with only expressive personality traits (S2). This was due to the fact that in Study 1, expressiveness turned out low when it was not specifically prompted. By including two conditions with expressive personality traits, we aimed to create more variation in expressive behaviors. The order of the five scenarios was randomized for each participant. The order of the five messages within each scenario was kept fixed, as the sequence reflected the unfolding dialogue and increasing severity of the patient's objections.

4.1.3 Materials

First, we assessed demographic information and participants' attitudes toward emerging technologies, AI-supported systems, and physiotherapy on 5-point scales [1 "very negative", 2 "rather negative", 3 "neutral", 4 "rather positive", and 5 "very positive"]. In addition, we asked participants about personal experiences with physiotherapy [1 "very negative", 2 "rather negative", 3 "neutral", 4 "rather positive", 5 "very positive", and 6 "not applicable/never had physiotherapy"]. These variables were included as potential control variables.

To rate the agent's messages regarding assertiveness, we adapted a scale from Babel et al. (2021) (A1–A4). Moreover, we created a scale for perceived expressiveness, including overall expressiveness (E1), facial expressiveness (E2), and emotional speech (E3). To measure perceived persuasiveness, we used the single-item measure "If I were in this position, I would have been convinced by the robot" (P1). We kept the number of items short, as each scale would be administered 25 times in total to each participant (see Section 5.1.3 *Study Design*). The questionnaire utilized a 7-point Likert scale ranging from "completely disagree" to "completely agree" to assess participants' responses. Table 4 presents the rating scales.

4.1.4 Procedure

Participants took part in the online study through a participation link. First, participants gave informed consent and were introduced to the physiotherapy use case through a detailed description. After filling out the pre-survey, participants were presented with rating guidelines that explained the relevant constructs under investigation (*assertiveness* and *expressiveness*), as well as the rating procedure. For each scenario, all five agent messages had to be rated. After each scenario was evaluated, the survey concluded. The mean study duration was 58 min.

TABLE 4 Rating scales for perceived assertiveness, expressiveness, and persuasiveness.

Code	Item text
Assertiveness	
A1	The message is formulated clearly and directly, without vague or uncertain wording.
A2	The message is decisive.
A3	The message is motivating.
A4	The message demonstrates an appropriate level of assertiveness.
Expressiveness	
E1	The general expressiveness (body language) of the message is adequate.
E2	The message uses facial expression adequately.
E3	The message uses emotional speech (speed) adequately.
Persuasiveness	
P1	If I were in this position, I would have been convinced by the robot.

4.1.5 Analysis

The behavior generation of GSAs is non-deterministic, meaning that conversational outputs might differ even if the input stays the same. To assess the robustness of the selected conversations, we conducted a computational replication analysis using the original model (ChatGPT-3.5), a newer model from the same platform (ChatGPT-4.1), and a model from a different platform (Claude 3.5 Haiku). For each LLM, the five scenarios were generated 100 times using identical prompts. Lexical similarity of these alternate conversations to the original Study 2 scenarios was assessed using TF-IDF cosine similarity, as suggested by other researchers (Celikten and Onan, 2025; Qurashi et al., 2020). Internal lexical similarity for GPT-3.5 was moderate to high (0.644–0.730), clearly exceeding a lexical similarity of 0.296 compared with a baseline prompt ("You are a social robot that acts as an advisor with the goal of persuading your human interaction partner on different topics"). External similarity was lower but still substantial for GPT-4.1 (0.558–0.615) and Claude 3.5 Haiku (0.581–0.693). Overall, the results suggest that the prompts produce broadly similar lexical content across repeated generations with the same model. Similarity was lower, but still substantial, across different LLMs. This supports the stability and replicability of the scenarios despite some model-related output variability. The corresponding Python scripts are available on GitHub (see text footnote 1).

Statistical analysis was conducted with the R tool. The reliability and factor structure of the scales to measure perceived assertiveness and perceived expressiveness were assessed using *Confirmatory Factor Analysis* (CFA). A multilevel CFA was conducted with observations nested within participants. The model demonstrated good fit to the data ($CFI = 0.962$, $TLI = 0.939$, $RMSEA = 0.073$, $SRMR-within = 0.058$, $SRMR-between = 0.056$), supporting the proposed two-factor structure. Factor loadings were strong for both scales, with standardized loadings ranging from 0.78 to 0.89 for perceived assertiveness and from 0.48 to 0.99 for perceived expressiveness. Reliability was evaluated using *McDonald's Omega*. This measure is more suitable for scales with a smaller number of items, as well as more accurate and consistent with latent variable modeling compared to *Cronbach's Alpha* (Dunn et al., 2014). The omega coefficients indicated high internal consistency for both scales (Perceived Assertiveness: $\omega = 0.94$; Perceived Expressiveness: $\omega = 0.87$).

To test Hypotheses H1–H3, the data were clustered by participants and transformed into long format. That is, each row in the dataset represented one rated agent message. Multilevel Structural Equation Modeling (SEM) was conducted to test the proposed model structure. This approach is suitable for mediation analysis (Koschate-Fischer and Schwille, 2022) and offers advantages to regression-based approaches regarding more detailed analysis of error terms and more statistical power (Breitsohl, 2019), fewer restrictions (Hayes and Rockwood, 2017; Pek and Hoyle, 2016), and parsimony (James et al., 2006). It is also useful to analyze within-subject dynamics (e.g., changes of perceptions across different scenarios) by applying repeated-measure approaches (Newsom, 2017).

In the multilevel SEM, Level 1 described within-subject effects and Level 2 modeled between-subject effects. In Level

1, all proposed main effects were modeled, following a 1-1-1 multilevel SEM approach. The covariance between perceived agent assertiveness and perceived agent expressiveness was estimated to account for any shared variance not explained by other predictors. In Level 2, participant-level effects that influenced perceived persuasiveness were accounted for. Alternative models were tested by exchanging predictors and dependent variables to examine the directionality of these relationships. Further, we included potential confounding variables such as message length, participant age, gender, and previous experiences with physiotherapy in alternate models. However, neither of these variables improved the model fit. In addition, to test the robustness of the multilevel SEM approach, linear mixed models were conducted, with messages being nested within scenarios, yielding similar parameters and significance levels as with the multilevel SEM approach.

The present study focused on Level 1 within-subject effects. Research indicates that high Level 1 observation counts increase power to detect fixed effects, with simulations showing that samples as small as 20 participants can still yield accurate estimates (Scherbaum and Ferreter, 2009). In the present study, 27 participants generated 675 message-level observations nested within participants, which provides a sufficient Level-1 sample size for the estimation of within-subject effects.

4.2 Study 2: results

To analyze the variable structure of the proposed model, a multilevel SEM model was estimated using restricted maximum likelihood estimation (Figure 2). The model included 26 parameters and was based on 675 observations (agent messages) across 27 clusters (participants). The model yielded a good fit ($CFI = 0.997$, $TLI = 0.941$, $RMSEA = 0.063$, $SRMR_{within} = 0.008$).

Perceived assertiveness had a large direct effect on perceived persuasiveness ($\beta = 0.735$, $p < 0.001$). Perceived expressiveness also significantly impacted perceived persuasiveness, albeit with a small effect size ($\beta = 0.175$, $p < 0.001$). *Self-knowledge* did not have a direct effect on perceived persuasiveness ($\beta = -0.025$, $p = 0.412$), but showed a medium-sized indirect effect ($\beta = 0.288$, $p < 0.001$). *Self-knowledge* also impacted perceived assertiveness ($\beta = 0.323$, $p < 0.001$) and perceived expressiveness ($\beta = 0.288$, $p < 0.001$) with medium effect sizes. This supports the hypothesized mediation model (H1). *User-knowledge* did not directly impact perceived persuasiveness ($\beta = -0.064$, $p = 0.516$), but had a small indirect effect ($\beta = 0.121$, $p < 0.01$). Availability of *user-knowledge* also led to a small increase in perceived assertiveness ($\beta = 0.137$, $p < 0.01$) and perceived expressiveness ($\beta = 0.115$, $p < 0.05$). These findings are consistent with the hypothesized mediation (H2). In contrast, *context-knowledge* showed neither a direct effect ($\beta = 0.016$, $p = 0.570$) nor an indirect effect on perceived persuasiveness ($\beta = 0.054$, $p = 0.157$). Similarly, *context-knowledge* had no significant impact on perceived assertiveness ($\beta = 0.075$, $p = 0.108$) or perceived expressiveness ($\beta = -0.006$, $p = 0.898$). These results fail to support the proposed mediation (H3).

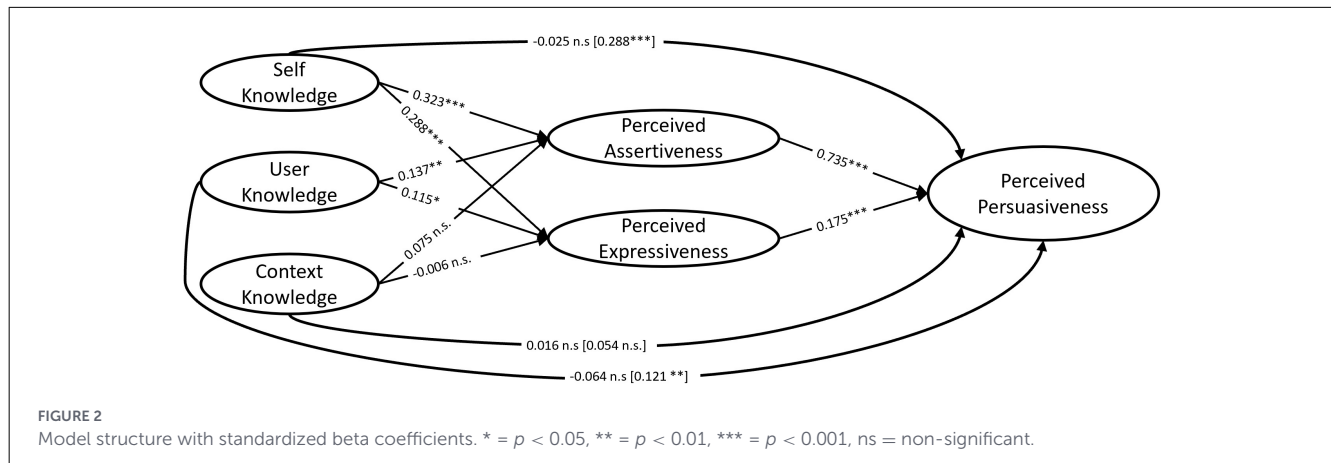
4.3 Study 2: discussion

The goal of Study 2 was to investigate whether an agent's available knowledge affected perceptions of the agent's persuasive behavior. Hence, we conducted an online study to test whether agent *self-*, *context-*, and *user-knowledge* affect third-party raters' perceptions of assertiveness, expressiveness, and persuasiveness. The results speak to the strong impact of perceived assertiveness on perceived persuasiveness, with small effects observed for perceived expressiveness. This aligns with previous research that observed positive effects of agent assertiveness (Bai et al., 2025; Chidambaram et al., 2012; Paradedda et al., 2019b; Thomas and Vaughan, 2018) and expressiveness (Chen and Fragomeni, 2019; Ma et al., 2025) on persuasion. The lower effect sizes for expressiveness in our findings might stem from the hypothetical nature of the scenarios, as a physically embodied robot platform could potentially exert a stronger impact on participants' perceptions by expressing itself more vividly through vocalization and non-verbal means (Admoni et al., 2016; Banna et al., 2025; Chidambaram et al., 2012; Ham et al., 2015).

The agent's *self-knowledge*—operationalized through assertive and expressive characteristics—had medium-sized effects on the agent's perceived assertiveness and expressiveness. As there was an indirect, but no direct effect on perceived persuasiveness, perceived assertiveness and expressiveness fully mediated the effect of *self-knowledge* on perceived persuasion effectiveness. These results align with previous research that found that LLM-based GSAs could successfully adapt their personality based on knowledge configurations (Banna et al., 2025; Frisch and Giulianelli, 2024).

User-knowledge—operationalized by information about the patient's advanced age and past profession—significantly predicted perceived assertiveness and perceived expressiveness of the agent. Again, a full mediation was observed, as there was no direct effect on perceived persuasiveness, but a small indirect effect, supporting H2. However, these results had less profound effect sizes compared to *self-knowledge*. The importance of personalization in this study could have been deemed less relevant than in other research (Lubos et al., 2024; Matz et al., 2024), as variations were potentially not strong enough. A reason for that could be that in our study, raters were unaware of the patient's actual age, which represents a methodological limitation. We could have addressed this issue by providing raters with more comprehensive profiles of the patient when presenting the scenarios.

Context-knowledge—operationalized by information about physiotherapy benefits and awareness of time of day—did not significantly impact perceived assertiveness, expressiveness, and persuasiveness. This is despite other research that has observed increased persuasiveness in agents with more topic knowledge (Khan et al., 2024). Plausibly, the manipulation of *context-knowledge* brought some methodological limitations. First, including time of the day simply did not change the agent's behavior apart from its greeting, as observed in the qualitative analysis of Study 1. Second, in conditions that did not explicitly prompt *context-knowledge*, similar information was already inherently available to the model—although potentially less salient. More



specific information that the GSA could not inherently know—for example, the contents of an upcoming physiotherapy session—could have been a much more effective manipulation. Future studies could also provide raters with more context information to help them accurately assess whether the agent acted in a responsible manner.

The effects of perceived assertiveness and expressiveness on perceived persuasiveness align with dual-process models of persuasion such as the Elaboration Likelihood Model (ELM) (Petty and Cacioppo, 1986). The ELM predicts that peripheral cues—such as assertive and expressive characteristics—can enhance persuasion when recipients engage in lower-effort processing. Our findings are consistent with this notion, as human raters appear to have relied on such cues when judging the persuasiveness of the agent's messages. Cialdini (2014) principles of authority and liking provide another potential explanation: assertiveness can function as a cue for authority, while expressiveness enhances liking and social presence, both of which are known to strengthen persuasive impact.

5 General discussion

In two exploratory studies, we analyzed persuasive agent messages and how the availability of different types of knowledge configurations might impact a GSA's persuasiveness in a therapy motivation use case. Results of Study 1 suggest that the availability of knowledge prompts may lead to differences in persuasive behavior. Study 2 further supports this, by highlighting that *self-knowledge* and *user-knowledge* shape third-party raters' perceptions of an agent's persuasive behaviors.

Personality traits included in *self-knowledge* prompts were found to be particularly important, as corroborated by existing studies featuring LLM-based agents (Frisch and Giulianelli, 2024). Our qualitative analysis further supports this: assertiveness-related prompts led to more consistent assertive behavior across scenarios, even though assertive behavior was also present in scenarios without such prompts. The qualitative analysis further revealed that the inclusion of *self-knowledge* about expressive personality traits was essential for the agent to display emotional expressions effectively.

User-knowledge exerted smaller effects on persuasive behaviors, which may be attributed to the relatively subtle nature of the manipulations used in this study. For instance, references to past professions and age might have been insufficiently salient to significantly influence perceptions. The small effects observed for cues that relate to the user's personal background suggest that more personally relevant factors, such as specific preferences or user personality traits (Gao et al., 2024; Lubos et al., 2024; Matz et al., 2024), as well as the user's health condition (Vonschallen et al., 2026d), could yield stronger effects. As observed in the qualitative analysis, the agent utilized *user-knowledge* effectively when included, especially when referencing age or past profession. However, these references were not consistently present across all scenarios, indicating that more detailed and personalized information might enhance the agent's persuasiveness.

The absence of significant effects for *context-knowledge* aligns with insights from the qualitative analysis: The time-of-day information influenced only the greeting behavior, indicating that the manipulation was not sufficiently impactful. Although the physiotherapy benefits prompt led to more detailed arguments in some scenarios, the GSA consistently referred to these benefits across most interactions. Plausibly, this was due to its inherent knowledge of the subject matter acquired during pre-training. This suggests that more contextually specific prompts, such as details about the content of a particular therapy session, may enhance the agent's context-sensitive behavior.

While context-related information was not significantly associated with perceived persuasiveness, it may influence how responsibly an agent conducts its persuasion attempts. In some scenarios, the agent confidently suggested alternatives to physiotherapy without verifying whether these options were actually available. This behavior reflects concerns raised by researchers regarding the risks of LLM hallucinations and the generation of false information (Chen et al., 2025; Ranisch and Haltaufderheide, 2025; Ciubotaru, 2025). Grounding an agent with relevant contextual knowledge may help mitigate these risks, for example through techniques such as *Retrieval-Augmented Generation* (Zhang and Zhang, 2025; Kumar and Swami, 2026) or the use of *Knowledge Graphs* (Lavrincovics et al., 2025; Wilcock et al., 2026). Further research

is needed to identify which information agents need to ensure responsible persuasive behavior that benefits human users.

6 Strengths and limitations

This paper presents a novel methodological approach to investigate the persuasive behavior of GSAs, combining qualitative and quantitative means. Because GSAs imitate human behavior based on vast amounts of human-generated data, their behavioral patterns may be investigated from a psychological perspective as well. As such, the current research switched the focus from predefined agent behaviors to observing autonomously generated persuasive strategies by using fixed human messages as input. While this method allowed us to compare different knowledge configurations in a safe and controlled manner, it also raises questions about the validity of the interactions for real-life physiotherapy settings, where human messages have higher variability. However, the intent behind the scenarios was not to create universal settings for physiotherapy motivation—as this would have been impossible due to nearly unlimited possibilities in open-ended interactions. Rather, the goal was to use a specific example with high relevance as a means to investigate the agent's autonomous decision-making. Hence, in order to observe which persuasive strategies and behaviors the GSA would choose on its own, we framed the motivation task relatively broadly without specifying behavioral rules. In more applied settings, future research should focus more on the effects of specific behavioral rules (e.g., using at most three persuasion attempts). Such studies should also equip the agent with a broader range of non-verbal expressive capabilities than the purely text-based approach implemented in the current work. Nevertheless, the present work lays the foundation for future research in such directions.

Another strength lies in the mixed-method approach applied in the current research. Not only were agent behavioral patterns analyzed from a qualitative perspective, but also by using third-party ratings to evaluate the agent's perceived assertiveness, expressiveness, and persuasiveness. This second study had the advantage of high statistical power through extended within-subject comparisons. In real-world human-agent interactions, such a design would have been difficult to deploy, as participants would have to engage in the same decision task with multiple variations of the same agent, which would be tiring and confusing compared to third-party ratings with more personal distance. As a result, this approach also introduced a number of limitations. It is unclear if participants would have actually been persuaded by the agent, as only perceived persuasiveness was measured. Further, using text-based scenarios might have impacted experimental realism, which could explain why only small effects of perceived expressiveness on perceived persuasiveness were observed. In hindsight, creating video-based scenarios in a similar setting would have made the situation more relatable, which we highly recommend for future research.

A further limitation is that only one specific LLM—ChatGPT-3.5—and one output of this model was used to create the persuasive

scenarios. Using the same model allowed for a better investigation of the effects of different kinds of available knowledge, but may have decreased generalizability. Other models that were trained on different data—or an alternative conversation of the same model—could have generated different outputs. Hence, we conducted a computational *post-hoc* analysis to compare text similarities with different models (see Section 4.1.6). This simulation-based analysis showed that there are substantial lexical similarities between scenarios generated by different models, but fewer similarities than when using the same model to generate multiple scenarios. This connects to recent work that analyzed inner- and inter-LLM writing similarity for thousands of prompts, finding that texts from the same model are more similar to each other than to texts from different models (Smith et al., 2025). The messages used for the scenarios had high lexical similarities to messages generated by the same model (ChatGPT-3.5) and other LLMs (ChatGPT-4.1, Claude 3.5 Haiku), indicating some generalizability of our results. However, future research should empirically compare different models in terms of their generated behavior to confirm this.

7 Conclusion

The present research provides valuable insights into the behavioral patterns of persuasive GSAs. Beyond the substantive findings, it also contributes a methodological paradigm for studying GSAs: Because of the probabilistic and opaque nature of generative AI systems, their outputs—much like human behavior—must be studied through empirical observation (Vonschallen et al., 2026a). By comparing responses of agents with varying knowledge configurations to fixed human messages, we can conduct such observation in a controlled manner.

From an applied perspective, the findings suggest that knowledge configuration may be a key lever for shaping not only the persuasiveness of generative agents, but also the responsibility of their behavior. In the physiotherapy context, providing agents with the right amount of *self*-, *user*-, and *context-knowledge* may help them motivate patients in ways that are supportive, adaptive, and less likely to produce harmful recommendations (Vonschallen et al., 2026d). More broadly, this principle extends to other domains in which generative agents can positively influence human decision-making, such as motivating students to learn. At the same time, restricting access to sensitive or strategically exploitable knowledge may reduce the harmful impact of misaligned agents. Taken together, these insights may inform future developments of GSAs that are both effective and aligned with human autonomy and wellbeing.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by the Ethics Committee of Bielefeld University. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

SV: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. RH: Conceptualization, Investigation, Methodology, Writing – review & editing. TS: Conceptualization, Supervision, Writing – original draft, Writing – review & editing. FE: Conceptualization, Supervision, Writing – original draft, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships

that could be construed as a potential conflict of interest.

Correction note

This article has been corrected with minor changes. These changes do not impact the scientific content of the article.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

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