The Road to AI Companionship: Designing a Sentient AI Agent for Enhanced Driving Experience*

Mihai Duguleană and Răzvan Gabriel Boboc

Abstract— **Artificial intelligence (AI) integration in the automotive field primarily focuses on automation and driver assistance. However, the emergence of sentient AI agents offers new possibilities for enhancing user experience through interactive companionship. Recent trends indicate a growing interest in AI-driven conversational agents beyond traditional voice assistants, fostering real-time emotional intelligence and contextual understanding. This paper proposes an AI model designed to function as an in-vehicle AI companion, capable of emotional intelligence, real-time decision-making, and personalized engagement. Our approach leverages a large language model (LLM), combined with a rule-based framework, to create a robust AI companion that dynamically adapts to human behavior. The system is optimized to run on commercially available hardware, making it accessible for widespread adoption.**

The proposed AI agent can engage in meaningful conversations, provide weather updates, road conditions, current news, and location-based insights, such as nearby tourist attractions and landmarks. The methodology includes a mixed evaluation strategy based on a Technology Acceptance Model (TAM) with five variables encompassing simulated driving environments and real-world user testing. The findings suggest that incorporating sentient AI agents in vehicles significantly improves driver satisfaction, situational awareness, and emotional well-being, paving the way for future advancements in human-centric AI automotive applications. With a focus on real-time adaptability and naturalistic interactions, this research demonstrates the feasibility of AI companionship in modern vehicles, making transportation safer, more engaging, and more intuitive for drivers and passengers alike.

I. Introduction

AI has been rapidly transforming multiple industries, and the automotive sector is no exception. Traditional AI implementations in vehicles have focused largely on automation, navigation, and driver assistance. However, the emergence of sentient AI agents represents a new paradigm shift, enabling vehicles to interact dynamically with passengers beyond functional support. These AI-driven companions aim to enhance user engagement, provide personalized insights, and foster trust in intelligent transportation systems.

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The increasing demand for context-aware and emotionally intelligent AI agents in vehicles stems from the growing emphasis on human-centric AI design [1]. Instead of serving solely as an information delivery mechanism, modern AI systems are expected to comprehend user emotions, adapt to behavioral patterns, and sustain engaging conversations [2]. Several studies have explored conversational AI and its application in human-machine interactions, emphasizing the importance of trust, adaptability, and contextual awareness [3].

Moreover, the evolution of blockchain-powered AI projects in 2024 has introduced decentralized infrastructures for AI agents, allowing digital avatars to function as revenue-generating assets. Projects such as Virtuals.io [4], Creator.bid [5], and Io.net [6] have demonstrated novel frameworks for AI-driven content generation and marketplace interactions. These advancements further reinforce the necessity of integrating sentient AI agents within automotive environments, fostering digital companions capable of both practical assistance and personalized engagement.

The literature on AI-driven in-vehicle companionship can be clustered into several research areas. One of the closest to this study is related to conversational AI and emotional intelligence. Liew et al. ([2]) discuss the role of perceived intelligence and anthropomorphism in AI-driven conversations, highlighting how human-like AI responses influence user acceptance and trust. This study aligns with our approach to designing emotionally aware AI companions. Mallol-Ragolta et al. ([7]) focus on affective dialogue management, demonstrating how AI agents can modulate speech patterns and responses based on user emotions. This aligns with our use of a rule-based framework to personalize in-vehicle conversations.

When it comes to cognitive AI models and sentient agents, Candiotto ([8]) explores the philosophical and cognitive dimensions of AI sentience, investigating whether digital entities can exhibit awareness and intentionality. Our study builds upon these findings by using a state-of-the-art LLM that integrates adaptive behavioral modelling into the AI agent's decision-making processes. Xie et al. ([9]) present human-like driver modelling using reinforcement learning, supporting our argument that AI companions can enhance naturalistic user interactions in vehicles.

Situational awareness and user trust were handled by several studies, such as the one presented by Thill et al. [10], in which they examine the impact of AI's perceived intelligence on driver situational awareness, revealing how drivers alter their behavior when interacting with an AI-driven assistant. This is highly relevant to our evaluation framework, where AI response adaptability and predictive accuracy play crucial roles. Lawson-Guidigbe et al. ([11]) explore user trust in AI-driven companions, emphasizing how factors like explainability and reliability affect long-term user engagement. These insights are critical for designing an AI agent that fosters trust and meaningful interactions.

II. Research Methodology

A. *Objectives*

This study aims to evaluate the effectiveness of a sentient AI companion in vehicles by analyzing user interaction, emotional engagement, and overall satisfaction. The key objectives of this research include:

1. Assessing user satisfaction with AI-generated conversational experiences in real and simulated driving conditions.
2. Evaluating the effectiveness of the AI avatar's expressiveness in creating a more immersive experience.
3. Identifying the impact of AI companionship on driver awareness and emotional well-being.

B. *Tools and Experimental Setup*

The physical testing took place in a 2014 Hyundai i40, a vehicle that lacks a built-in touchscreen (see Fig. 1). To integrate the AI agent into the driving experience, the application was deployed on a web server using the met4citizen TalkingHead library [12].

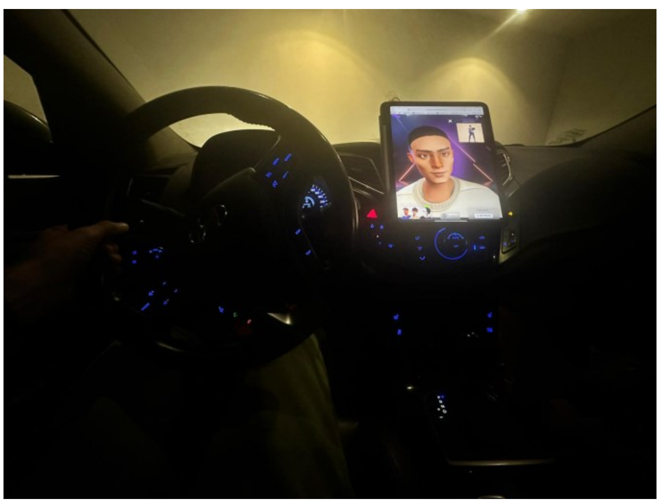

Figure 1. Physical evironment setup

The TalkingHead library was built upon the Ready Player Me avatar framework, which is animated via the Three.js library. We tested both Elevenlabs and Microsoft TTS for natural text-to-speech synthesis and settled for the latter. The language of choice was English. The avatar was accessed via a browser on an iPad Pro tablet, which was securely mounted within the vehicle. The iPad Pro, equipped with the Apple M2 chip and a Liquid Retina XDR display, provided a smooth experience for rendering the avatar. Its high-resolution screen and powerful GPU acceleration ensured real-time AI and driver interaction. The AI agent provided real-time conversational assistance, responding to user queries regarding weather conditions, road updates, news, and location-based insights. The AI's facial and lip animations were displayed on the tablet to enhance visual engagement based on the Mixamo addon. The avatar used is presented in Fig. 2.

Figure 2. Used avatar

Figure 3. Virtual evironment setup, with the MOOG platform and the mounted driving simmulator

The virtual testing was conducted on a custom-built immersive driving simulator with a MOOG inertial platform (see Fig. 3), which can replicate realistic vehicle movements and road conditions. The control of the platform was done with MATLAB Simulink (see Fig. 4).

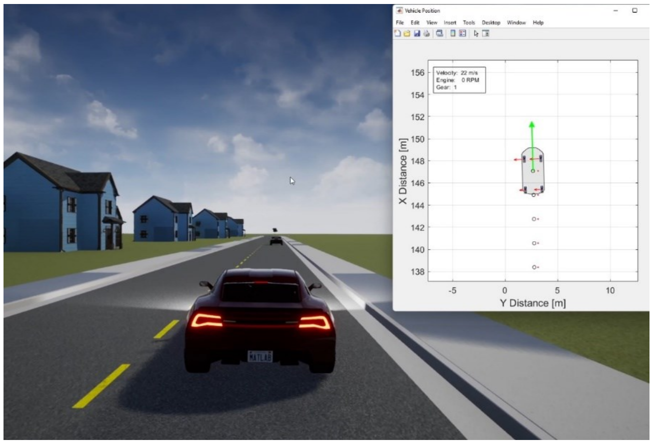

Figure 4. Virtual evironment setup

We have used a Dell XPS 17 laptop equipped with an NVIDIA RTX 4080 GPU and 64GB of RAM to deploy a local LLM, the llama 13B model. Further optimization (vLLM and FlashAttention) allowed for real-time response generation, keeping latency below 200 milliseconds per query. This ensured low-latency responses and real-time AI interactions. The virtual test environment was generated using a simple loop circuit. The AI companion interacted with users in this simulated setting, offering personalized conversation, emotional recognition, and real-time information updates. To enhance context-awareness and behavioral adaptation, a rule-based framework was developed as a structured prompt for the llama 13B model.

This framework acted as a guiding mechanism, ensuring the AI responded appropriately to various driving scenarios and driver behaviors. It consisted of several predefined conversational pathways, ensuring AI responses remain relevant to vehicle-related topics (traffic, weather and entertainment discussion). We also described the idea of dynamically recognizing user intent and adjusting responses based on detected driver emotions. Moreover, the agent can modify its suggestions based on driving conditions, location, and past interactions. Last but not least, we employed safety filters – a limitation that prevents complex discussions when the car is in motion in order to limit driver distraction.

C. Data Collection and User Feedback

A pilot study was conducted with 22 participants: 18 males and 4 females. All of them have a good English level – they feel comfortable using this language in their interaction with the Ai agent. The participants were stratified based on their age, driving experience, and familiarity with AI-driven systems.

Participants were divided into three age groups: 8 participants between 18-30 years, 10 participants between 31-50 years, and 4 participants aged 51 years or older. Driving experience was also categorized, with 5 novice drivers (less than 2 years of experience), 12 experienced drivers (2-10 years of experience), and 5 veteran drivers (10+ years of experience). Additionally, participants were classified based on their familiarity with AI assistants, where 6 participants had no prior experience, 10 participants had limited experience (e.g., using Alexa or Siri), and 6 participants had extensive experience with AI-driven systems.

A Technology Acceptance Model (TAM) questionnaire rated on a Likert scale from 1 to 7 was distributed after the driving sessions to measure users' satisfaction with interacting with the AI avatar. TAM has been used before in evaluating AI systems in e-commerce [13], law [14], construction [15], and even agriculture [16]. To evaluate the effectiveness of the AI system, we measured perceived usefulness, ease of use, attitude towards use, behavioral intention, and system trust, as presented in Table 1. To ensure continuity, each variable was measured via 2 different questions.

TABLE I. TAM QUESTIONNAIRE

Variable	*Question*	*Scale (1-7)*
Perceived Usefulness	The AI companion improves my driving experience.	1 (Strongly Disagree) - 7 (Strongly Agree)
	The AI assistant provides useful and relevant information while driving.	1 (Strongly Disagree) - 7 (Strongly Agree)
Perceived Ease of Use	The AI system is easy to interact with.	1 (Strongly Disagree) - 7 (Strongly Agree)
	The AI interface is intuitive and simple to use.	1 (Strongly Disagree) - 7 (Strongly Agree)
Attitude Towards Use	I enjoy using the AI companion.	1 (Strongly Disagree) - 7 (Strongly Agree)
	The AI assistant enhances my overall driving experience.	1 (Strongly Disagree) - 7 (Strongly Agree)
Behavioral Intention	I would use the AI companion frequently.	1 (Strongly Disagree) - 7 (Strongly Agree)
	I intend to use the AI assistant in future driving experiences.	1 (Strongly Disagree) - 7 (Strongly Agree)
System Trust	I trust the AI's recommendations and responses.	1 (Strongly Disagree) - 7 (Strongly Agree)
	I feel confident that the AI system operates reliably and safely.	1 (Strongly Disagree) - 7 (Strongly Agree)

III. Research Results

The mean scores for the five key variables (*Perceived Usefulness*, *Perceived Ease of Use*, *Attitude Towards Use*, *Behavioral Intention*, and *System Trust*) provide insights into participants' general attitudes towards the system (see Fig. 5). Similar variables have been investigated in other TAM studies [17-19].

The highest-rated variable was *Attitude Towards Use*, indicating that participants enjoyed using the AI system. This suggests a positive user experience and a high level of acceptance. *Perceived Ease of Use* and *System Trust* also received relatively high scores, reinforcing that users found the system intuitive and trustworthy. On the other hand, *Behavioral Intention* received the lowest mean score, which implies that while participants might have positive attitudes toward the system, they may not be fully committed to continued use or future engagement.

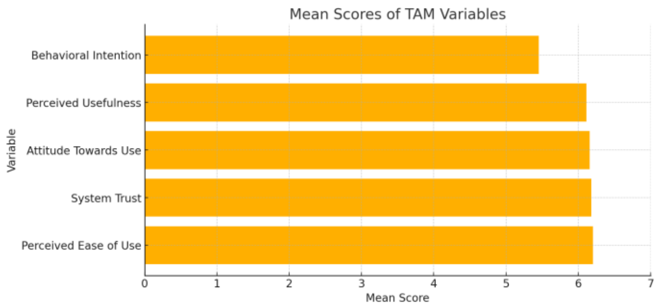

Figure 5. Mean scores for the 5 TAM variables

Users consistently reported that the AI enhanced their ability to stay informed about road conditions, weather, and navigation assistance. The availability of real-time, voice-assisted information reduced cognitive load, allowing drivers to focus on the road. However, a subset of participants expressed mild dissatisfaction due to occasional delays in response generation. These delays were more frequently noted in the physical driving environment compared to the virtual simulator, likely due to network latency when retrieving external data.

Users also found the tablet interface and voice assistant highly accessible, especially those with previous experience using AI-based assistants like Siri and Alexa. The iPad Pro's high-resolution display and touchscreen interactivity played a crucial role in enhancing usability, particularly in low-light conditions where drivers relied more on the visual representation of the AI companion. However, novice users (those unfamiliar with AI assistants) took longer to get accustomed to the system. Their initial interactions were hesitant, but most adapted within the first 5 minutes of use. This suggests a small learning curve that could be mitigated with tutorial-based onboarding.

Qualitative feedback revealed that personalization played a crucial role in user enjoyment. Participants who interacted with the AI companion frequently found the system to be engaging and entertaining, while those who used it only occasionally reported a more neutral stance. A common suggestion was the inclusion of customizable AI personalities to cater to different user preferences. Some participants preferred a more formal and concise AI assistant, while others wanted a casual, conversational companion. Another key observation is that participants who drive long distances (e.g., commuters, travelers) expressed higher interest in continued use compared to those who drive short distances (e.g., city drivers). This suggests that the AI companion is more valuable in extended trips, where continuous interaction and information delivery provide greater benefits. Additionally, first-time AI users were more hesitant to commit to future use, indicating that trust and familiarity development are crucial factors in long-term adoption.

Examining the distribution of responses provides a deeper understanding of how participants' opinions varied (see Fig. 6).

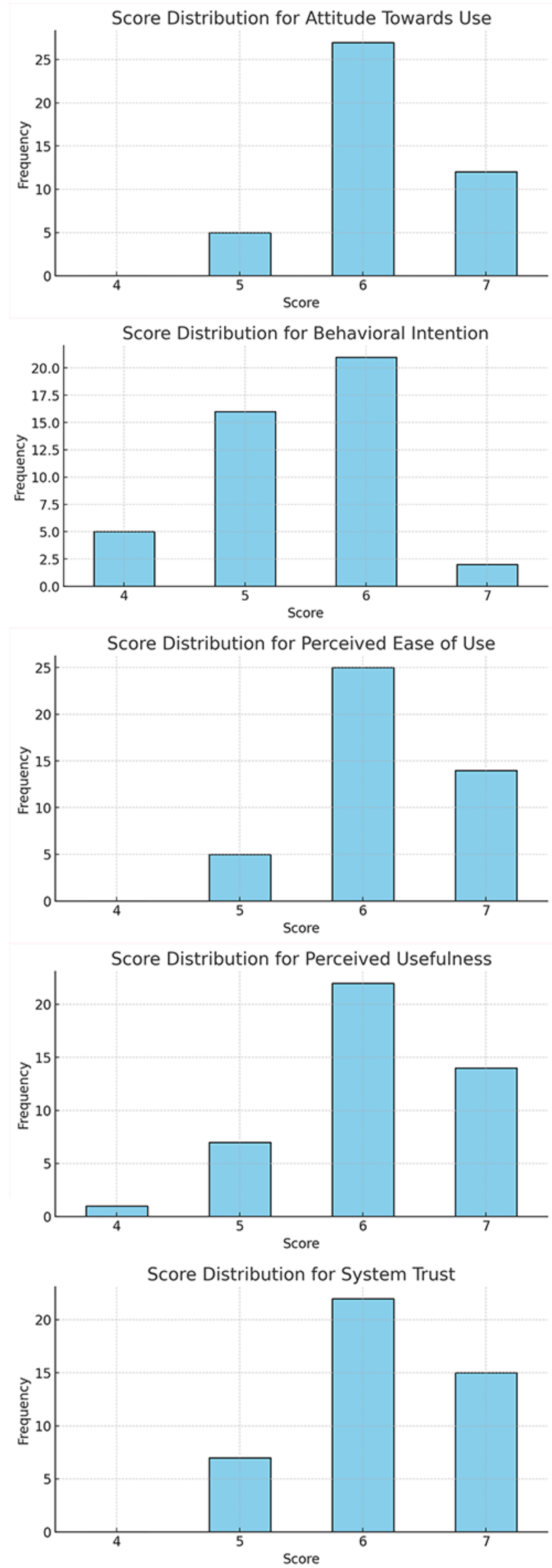

Figure 6. Distribution of scores for each of the 5 variables of the TAM questionnaire

The variable *Attitude Towards Use* had a significant number of high scores (6s and 7s), confirming that most users had a favorable attitude towards the AI system. *Perceived Ease of Use* also received mostly high scores, suggesting that the AI system's usability was well-received. *System Trust* exhibited a balanced distribution, with most responses in the 6-7 range, indicating that users generally trusted the system. *Perceived Usefulness* showed a mix of responses, with a few lower scores (4s and 5s), suggesting some variability in how useful users found the AI assistant. *Behavioral Intention* had the most diverse distribution, with a notable presence of lower scores (4s and 5s). This suggests some reluctance among users regarding long-term engagement with the system.

The results suggest that while users generally have a positive attitude, trust, and ease of use experience with the AI system, there is still room for improvement in *Perceived Usefulness* and *Behavioral Intention*.

According to several discussions carried out within the pilot study, participants observation and field notes, to enhance the first variable – *Perceived Usefulness*, the AI system should focus on more personalized recommendations, increased efficiency, and better integration with user needs. In a similar way, developers may need to add features that encourage long-term use, such as customization options, gamification, or better alignment with users' daily tasks in order to improve the second more “problematic” variable – *Behavioral Intention*.

System Trust exhibited the highest variability, with responses ranging from 3 to 7. Participants who were experienced with AI assistants showed higher trust levels, while those new to AI-based decision-making expressed skepticism. A notable concern was data reliability. Some users questioned whether the AI’s road condition updates were always accurate, especially in dynamically changing environments. Trust-building measures, such as explaining the AI’s data sources and decision-making process, could mitigate skepticism.

Fig. 7 presents the graphical representation of the correlation matrix between the TAM variables. The heatmap provides a clear visual understanding of how each variable is related to the others, with color gradients indicating the strength and direction of the correlations. *Perceived Usefulness* and *Behavioral Intention* have a strong positive correlation (0.67), indicating that participants who found the system useful were also more likely to intend to use it in the future.

Perceived Usefulness and *Attitude Towards Use* are moderately correlated (0.53), suggesting that perceived usefulness slightly influences how much participants enjoy using the AI. *Perceived Ease of Use* and *Perceived Usefulness* have a moderate correlation (0.50), showing that usability impacts how useful users perceive the system to be. *Attitude Towards Use* and *Behavioral Intention* show a positive correlation (0.34), meaning that those who enjoy using the system are more likely to continue using it. *System Trust* has a weaker correlation with other variables, though it still shows a slight relationship with *Behavioral Intention* (0.36) and *Perceived Usefulness* (0.25).

We conclude that the strongest relationships are between *Perceived Usefulness* and *Behavioral Intention*, as well as *Perceived Usefulness* and *Attitude Towards Use*, reinforcing that a system's usefulness significantly influences user engagement and enjoyment.

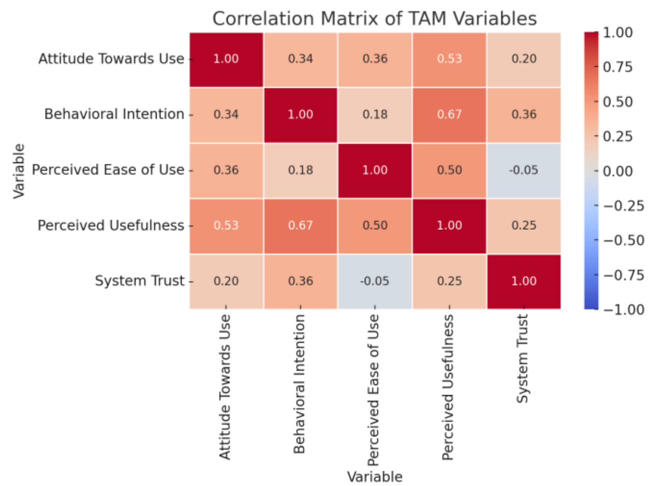

Figure 7. The correlation matrix between the TAM variables

IV. Conclusion

The analysis of the TAM questionnaire provided valuable insights into user perceptions regarding the AI system. The results indicate a generally positive attitude towards the system, with high scores in *Perceived Ease of Use*, *Attitude Towards Use*, and *System Trust*. Users found the AI interface intuitive and enjoyable, suggesting a well-designed and user-friendly experience.

However, *Behavioral Intention*, which measures the likelihood of continued use, received relatively lower scores. The correlation analysis showed that *Perceived Usefulness* had the strongest impact on *Behavioral Intention* (0.67). This suggests that users are more likely to continue using the AI system if they perceive it as beneficial in their daily activities. Future improvements should focus on increasing the AI’s practical value and relevance to users' needs.

Perceived Ease of Use and *Perceived Usefulness* were also positively correlated (0.50), confirming that a user-friendly system enhances the perception of usefulness. This reinforces the importance of maintaining a simple, intuitive interface to encourage adoption.

Although *System Trust* had a weaker correlation with other variables, its positive association with *Behavioral Intention* (0.36) suggests that trust plays a role in long-term engagement. Strengthening reliability and transparency in AI decision-making could improve user trust and retention.

While the system is well-received, enhancing its functional value and long-term engagement strategies should be prioritized. Addressing gaps in perceived usefulness and ensuring the AI meets user expectations will be crucial for fostering continued adoption. Future research could further explore customization options, personalization, and integration with daily tasks to enhance the AI companion’s role in vehicle-based interactions.

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