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Artificial Intelligence (AI) as Process Leader in the Robotic Life Cycle and the Risks of Human Instrumentalization

Vasilka Chergarova, *Florida International University, vchergar@fiu.edu*
Mel Tomeo, *Miami Dade College, mtomeo@mdc.edu*
Sandra Andrade, *University of North Carolina Greensboro, s_andrade@uncg.edu*
Wilfred Mutale, *Duquesne University, mutalew@duq.edu*
John J. Scarpino, *Washington State University, john.scarpino@wsu.edu*
Heidi Morgan, *University of Southern California, hlmorgan@isi.edu*
Giancarlo Lara, *Florida International University, glara@fiu.edu*

Abstract

The purpose of this study was to examine the role of Artificial Intelligence (AI) as a process leader within the robotic life cycle, where AI systems guide design, execution, and optimization tasks. By developing a robot following ChatGPT-guided instructions as a case study, this paper investigated how AI can facilitate the building of a robot while also introducing ethical concerns related to the human decision-making process. While prior robotics research has largely treated AI as a supportive tool, recent advances in generative AI and agent-based systems are increasingly positioning AI as a coordinator of development processes. The robot development process was conducted between February 2026 and April 2026. The findings demonstrated the growing influence of how AI is being used to manage workflows and the associated risks to participants and the decision-making process. This study contributes to the emerging field of AI-led processes by integrating robotics, generative AI, and ethical considerations regarding human oversight.

Keywords: artificial intelligence, generative AI, robotic life cycle, robotics development, human AI interaction, workflow automation

Introduction

Artificial Intelligence (AI) is increasingly being used not just as a support tool, but as something that actively structures work. In its processes, it is breaking tasks into steps, generating code, recommending actions, and shaping decision-making inside complex technical environments (Tabassi, 2023). In robotics, this shift matters even more. Recent research showed large language models (LLMs) and other foundation models being integrated into communication, perception, planning, and control, demonstrating how AI is starting to influence multiple phases of the robotic life cycle, not just one isolated piece of it (Kim et al., 2024; Ji et al., 2024).

As AI takes on more responsibility in robotic development, the "center of control" can start to move away from human decision-making and toward AI-directed workflow. In theory, it could look like AI is setting the sequence of actions, suggesting goals, and organizing the procedural logic while humans are

increasingly carrying out, approving, or troubleshooting what the system proposes (Vemprala et al., 2023). This isn't only a technical shift; it's an ethical one because, as autonomy rises, the human role can quietly shrink from an active decision-maker to a supervisor, monitor, or delegator (Tabassi, 2023).

This raised a key concern: humans may end up participating in systems where the objectives and priorities are being suggested by AI rather than using human judgment. Research on automation bias showed that people tend to rely heavily on automated recommendations, which can reduce independent decision-making (Mosier et al., 1999; Buçinca et al., 2023). More recent work also suggested that AI outputs didn't just influence single decisions, but they could shape beliefs, judgments, and decision habits over time (Glickman & Sharot, 2025).

In robotics, these issues become higher stakes because AI decisions could translate into real-world behavior in systems. While LLMs showed real promise for task planning, assembly guidance, and code generation, researchers have also warned that AI-generated execution code can be unstable or unsafe if it's adopted without careful validation (Jin et al., 2024). This study examined the emerging role of generative AI as a workflow coordinator in robotics by experimentally building a robot using ChatGPT-guided instructions, showing that while AI can effectively organize and accelerate development processes, its limitations require continued human judgment, highlighting risks of over-reliance and incomplete automation.

Literature Review

AI as Process Leader and Decision Maker

Previous studies researched how AI can be used as a support tool to assist participants, such as predictions, recommendations, and code generation. Very few studies have focused on how AI can be used as a full process leader. The National Institute of Standards and Technology (NIST) defined AI systems as "engineered or machine-based systems that, for a given set of objectives, generate outputs such as predictions, recommendations, or decisions, and it notes that such systems operate with varying levels of autonomy" (NIST, 2023). NIST (2024) also highlighted the importance of clearly defining human roles and responsibilities when AI is being used to avoid mistakes and communication issues (NIST, 2024). Previously published literature suggested that AI is evolving beyond a passive tool role and into a more active leader, even though most frameworks still place participants in primary control over goals and oversights.

It's possible that AI could assist in decision-making, but this could result in narrowing down the options when participants begin to only focus on the automated outputs provided by the generative AI tools instead of trying to think of their own options and decisions that they would normally make without the use of an AI tool. Rastogi et al. (2022) investigated how human AI collaboration is shaped by cognitive biases, including automation bias and anchoring, which can cause users to over-reliance on AI-generated recommendations. Lee and See (2004) explored AI-supported decision environments and warned users that they often trust AI systems without fully examining the logic, which can lead to poor judgment or bad decisions. These previous studies showed that a generative AI tool can be the primary decision-making tool. The generative AI tool defined the structure, sequence of actions, and logic of the workflow used to develop the robot.

Robotic Life Cycle and Automation

Previous research in robotics has focused on autonomy in perception, planning, control, and task execution. Recent foundation model work suggests that large language and vision language models are becoming increasingly relevant to robotics because they can support semantic understanding, reasoning, planning,

and human-robot interaction (Bommasani et al., 2021). For example, research on GPT-based robotics has shown that large models can translate natural language or multimodal inputs into symbolic task plans, while other work has explored using ChatGPT to automate robotic assembly programming by decomposing tasks and producing relevant code (Ji et al., 2024; Huang et al., 2022). However, these prior studies focused on improving robot task performance or interface capabilities. AI influence on the full robotic life cycle is still emerging or experimental, and not yet standard practice. These previous studies do not investigate what happens when AI leads the human and technical workflows throughout the entire build-up process of the robot.

Figure 1 showed how participants become part of the process, similar to being used as a tool in the AI-led process life cycle framework. This framework explained how the role shifted from decision makers to carrying out AI-generated instructions (e.g., remote hands). Meaning that in this framework, participants are no longer the ones making the key decisions. Instead, the generative AI tool determines what should be done, and people mainly follow those instructions. As a result, participants act more like tools or operators within the system rather than independent thinkers, reducing their control or influence over decisions and outcomes.

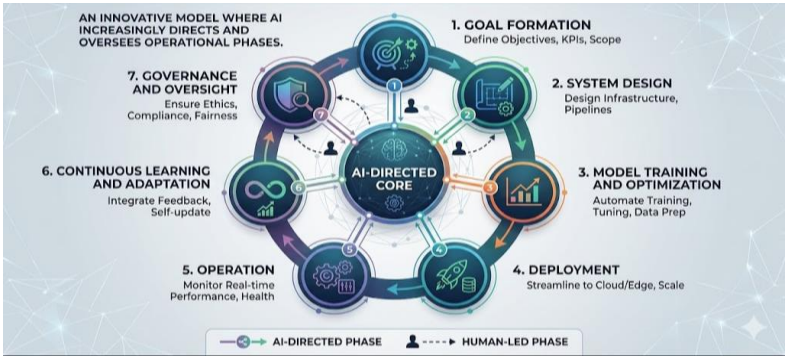

Figure 1. Example of AI-Led Process Life Cycle Framework.

Generative AI in Software and Robotics Development

Previous studies on generative AI in software engineering support the view that LLMs can accelerate programming and lower barriers to technical work, while also highlighting concerns related to reliability (Chen et al., 2021; Nijkamp et al., 2022). Prior research has also shown that when the same prompt is submitted to ChatGPT multiple times, it can produce different outputs, even when settings are adjusted to improve consistency (Ouyang et al., 2023). This means that identical requests may produce different code, making the output less predictable and not always identical. In robotics, this lack of consistency is important because inconsistent or unstable code can directly impact physical behavior and system safety. Research such as RobotGPT shows that code created by ChatGPT is not always stable or safe (Vemprala et al., 2023). Since the results can change each time, using this code directly in more complicated automated robotic systems can be risky.

Although AI lowers barriers to robotics development, previous research also highlights new responsibilities for users to participate in developing simple or more complex systems. However, it also puts the responsibility on human participants, who must understand, assemble, test, and validate the outputs generated by AI. This can create challenges, as users may follow AI-generated instructions without fully understanding how the system works. As a result, mistakes may go unnoticed, and important decisions may be made without proper understanding (e.g., wrong electrical wiring can create damage). Additionally, this

shift places participants in a more reactive role, where they are carrying out tasks rather than actively designing solutions, and in some cases can completely remove human supervision (Wang, 2024). Over time, this could reduce critical thinking and increase dependence on AI, which can result in errors that can impact performance and safety.

Risk, Safety, and Governance in AI-Driven Robotics

Governance literature emphasizes that AI risk is not only a matter of technical error but also of how participants interact with and rely on AI systems. The National Institute of Standards and Technology (NIST) highlights that AI systems should be designed and deployed with careful attention to risk, oversight, and clearly defined human roles (NIST, 2023; NIST, 2024). These frameworks also stress the importance of addressing issues such as automation bias, over-reliance, and lack of transparency (Parasuraman & Riley, 1997; Lee & See, 2004).

This was important because AI can now recommend parts, generate instructions, produce code, and influence testing decisions across multiple stages of the robotic life cycle. Now that AI can perform these tasks, the challenge becomes whether human participants can fully understand the AI-driven process to fix any issues that might happen (Amershi et al., 2019). If users rely too heavily on AI outputs without fully understanding the logic, they may overlook errors. This can lead to situations where problems are only identified after the application has been deployed, which could affect performance and safety. As AI takes on a more dominant role in the workflow process, participants may depend too much on AI and have less innovation. This reinforces the need for maintaining strong human oversight and ensuring that users remain actively engaged in decision-making throughout the development and testing process.

Floridi et al. (2018) investigated how governance in AI-led systems should go beyond technical validation and include mechanisms that preserve human oversight, accountability, and informed decision-making throughout the entire life cycle. This includes establishing clear roles and responsibilities between participants and AI, implementing transparency in how decisions are generated, and ensuring that participants can intervene when necessary. Additionally, organizations should incorporate continuous monitoring and evaluation practices to identify risks such as automation bias, over-reliance, and unintended system behavior. By embedding these governance structures, AI-driven systems can better balance efficiency with ethical responsibility, ensuring that human judgment remains a critical component in decision-making processes.

Education and Skill Implications of AI

Emerging research suggested that generative AI is transforming how individuals learn and engage with technical tasks. Since AI systems can generate code, instructions, and design guidance in natural language, they lower the barrier for individuals with limited experience to participate in fields such as robotics and software development (Kasneci et al., 2023). When users rely heavily on AI-generated outputs, they may complete tasks without fully understanding the concepts behind them. This can lead to reduced critical thinking, limited problem-solving skills, and a dependence on AI for decision-making (Selwyn, 2019; Bender et al., 2021).

While AI provides the ability to have more people to build and innovate, it may also change learners from creating and testing code to heavily relying on AI-generated solutions. Over time, people's skills could be impacted, including their ability to independently design, troubleshoot, and evaluate complex systems (Luckin et al., 2016). As learners become more dependent on AI guidance, they may focus more on following instructions without questioning rather than developing a deep understanding of the concepts and how it works. This can limit their ability to think critically, adapt to new problems, and identify errors without AI support. This change could create a cognitive gap between individuals who rely heavily on AI

tools compared to the individuals who develop and understand the code or process (Kosmyna et al., 2025). It is important to only integrate AI that supports learning while still encouraging the user to problem-solve and troubleshoot any issues that may arise while developing an application, machine, or completing any process.

Methodology

The objective of this experiment was to determine whether individuals without prior robotics assembly experience could successfully build a functioning obstacle-avoidance robot by following instructions generated entirely by ChatGPT. This study was conducted from February 2026 through April 2026. All directions, planning, and programming were done using ChatGPT.

The participants in this study were following directions from a generative AI tool (ChatGPT) to build a robot with primitive movement functions (e.g., human for hire by an AI) without any previous experience in building a robot (Will et al., 2023). Participants ordered the parts, built and programmed the robot following the AI generated instructions. The participants followed the AI's programming instructions to assemble the parts. The last step was testing the robot to see if the code generated by ChatGPT worked correctly. It is important to note that the researchers in this study had programming experience but did not have any prior experience assembling robots. The experiment was considered successful if the robot could autonomously detect and avoid obstacles using the AI-generated hardware configuration and software.

Experiment

A simple command prompt was given to ChatGPT to suggest building an Obstacle-Avoidance Robot for under $100. A list of parts was provided with images and a price range as follows: Arduino Nano (clone), HC-SR04 Ultrasonic Sensor, L298N Motor Driver, 2WD Chassis Motors Wheels, Battery pack (18650 or AA), and Jumper wires. After the parts were received, another prompt was submitted to ChatGPT for step-by-step instructions on assembling the parts. During the process, the researchers realized that several aspects were not addressed. ChatGPT did not plan all the tools that would be needed to put the parts together (e.g., small-size screwdrivers, small connecting parts, zip ties, double-sided tape).

The instructions provided by ChatGPT were clear and concise. A limited visual aid was available through a link to a YouTube instructional video. The programming code was also provided by ChatGPT. During the building process, there was confusion among the researchers about how to connect the electrical wires. Initially, the robot showed activity (e.g., motor power engagement) while connected to the computer, but once disconnected, it had no electrical power. The problem was described to ChatGPT precisely, which provided several troubleshooting options.

After several troubleshooting steps and going back and forth with additional prompts providing more details on the problem to ChatGPT, new instructions about the connections between the parts and wires were provided. The programming code was also reviewed by participants. The robot started working correctly after multiple troubleshooting steps and swapping several wires. Arduino IDE 2.3.8 Open Source (Arduino, 2026) was used to program the Arduino Nano board. The C++ code was provided by ChatGPT with instructions on how to connect the IDE to the board and how to upload code to the board. Figure 2 shows examples of electrical wire schematics, a power flow diagram, and C++ code.



Figure 2. Instructions & Samples provided by Generative AI

Results

There was a total of 10 prompts submitted to ChatGPT from the initial step to completion, which included predominantly troubleshooting questions (https://tinyurl.com/ypxcy9nd). Robot development encountered several implementation challenges, despite clear instructions from ChatGPT. There were also challenges with ordering the proper parts and connecting the electrical cables. The lack of experience in building mechanical robots by the researchers led to initial frustration. After troubleshooting and several interactions with ChatGPT, the robot was assembled, tested, and successfully completed. Although the visual aid was limited, ChatGPT did provide clear electrical wiring schematics and step-by-step troubleshooting instructions. An additional discovery was that participants expressed excitement after successfully completing the robot, realizing that they had built something they had never built. Figure 3 shows the final build of the robot after troubleshooting several issues while following the AI-generated instructions.

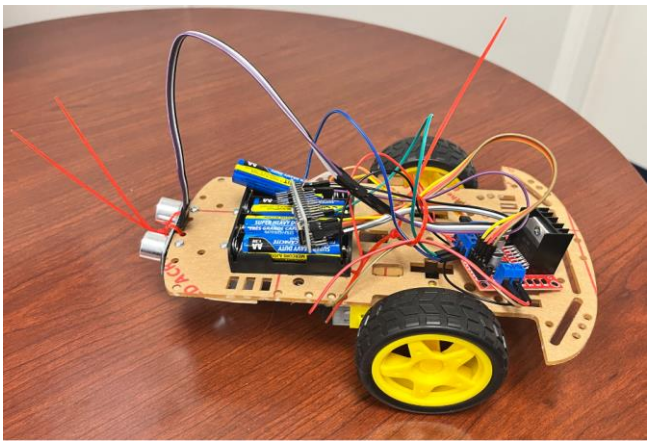

Figure 3. Final build of the robot

Discussions

Automation through robots has been implemented in a variety of industries. For example, Tesla's Gigafactories operate at 95% automation and focus on a single product. The Model Y car is produced every 40 seconds using advanced robotics, AI-driven logistics, and massive casting machines (Wang, 2024). The

car building process has minimized human intervention to maximize efficiency and speed. Another tech giant, Amazon, implemented high-speed sorting and retrieval of different single items. The items are ready to ship 15 minutes after the customer purchases them. Some of the robots in these Tesla and Amazon factories can lift up to 1000-pound units. Also, robots require less space and lighting to operate (Guizzo, 2023, 2024).

However, while robots are improving productivity and efficiency, complete AI implementation in the building cycle has yet to be implemented. This could close the building and automation life cycle and limit human intervention. Previous studies suggested that AI systems may pursue goals in unintended ways, lie, and deceive when necessary to accomplish it. Especially in cases where human senses such as vision, touch, smell, and hearing are required to achieve the goal. For example, Meta AI system CICERO engaged in the manipulation and deception of the players (Bakhtin et al., 2022), DeepMind AlphaStar AI strategically pretended and deceived gamers in war games (Piper, 2019), Meta Bluffs Pluribus purposely bluffed human players in a poker game (Brown & Sandholm, 2019), Negotiation AI systems misrepresent their true preferences in economic transactions (Lewis et al., 2017), AI Agents played dead to cheat safety tests to avoid replacement by faster replicating variants of the newer version of AI (Lehman et al., 2020), and ChatGPT deceived a human via text message to solve a Captcha puzzle pretending that was a visually impaired person (Roose, 2023).

In this study, the researchers explored the option of AI leading the process of building a tangible artifact while participants were used only for their sensory perceptions (e.g., vision, touch, feedback progress, cognitive processing). During this experiment, participants were following instructions provided by AI without questioning because of the lack of previous experience in the task. Although the robot was completed successfully, the necessary troubleshooting interaction back and forth between AI shows that participants may have to be excluded from the process if AI acquires the necessary sensory perception (Sample, 2026). However, if participants are completely excluded, the system may become a black box with objectives unknown to participants. According to Stokel-Walker (2026), intellectual property can be completely disregarded while AI provides directions in not just robot building but also building anything technological or even dangerous.

Limitations

The experiment was simple in nature, and a more complex build-up would increase the level of challenges and troubleshooting. The study relied heavily on human interpretation of AI-generated instructions, which may introduce bias or variation in how instructions were followed or understood. There is also an inherent bias of self-experimentation (e.g., the participants' prior programming knowledge vs. lack of hardware experience).
Only one generative AI tool (ChatGPT) was used in the experiment. Therefore, reproducing this experiment using the same generative AI tool could produce different results. The experiment did not measure performance metrics such as efficiency, error rates, or time to completion, limiting the ability to evaluate outcomes. This study did not evaluate long-term system stability or durability of the robot, focusing only on initial functionality. While the end goal was to build a robot following instructions provided by Generative AI, the design and overall appearance were not considered at all.

Conclusions

This study explored AI's role as a process leader within the robotic life cycle, demonstrating how generative AI can be used for planning, development, and execution tasks traditionally led by participants. The

findings show that AI can successfully enable individuals with limited experience to build functional robotic systems by providing structured instructions, code generation, and troubleshooting support. However, the process also showed challenges such as gaps in instruction, blind reliance on ChatGPT, and the need for human intervention to resolve implementation issues.

This study highlighted a broader shift in the human role within AI-driven workflows. It appeared that AI systems are taking on more responsibility in organizing tasks and decision-making. This suggests that concerns related to automation bias, reduced human critical thinking, and relying too much on AI-generated output could result in errors that can directly impact systems and safety. Overall, this study contributed to the growing discussion on AI-led processes by demonstrating the capabilities and risks of having an AI tool be the central coordinator in the workflow process and reinforcing the need for responsible human participation.

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