Generative-AI Assisted Implementation of an Under-Ride Lift Carrier for Autonomous Mobile Robots

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Abstract

This paper presents a generative-AI–assisted design and implementation of an under-ride lift carrier for autonomous mobile robots (AMRs). The system was developed using an AMR platform to enable automated docking, lifting, and transportation of wheeled trolleys in confined industrial environments. Generative artificial intelligence was utilized throughout the design workflow to synthesize mechanical concepts, optimize sensor placement, identify problem issues, and generate control-logic structures for reliable docking and load handling. The resulting prototype integrates a low-profile lift mechanism and AI-guided parameter tuning. In validation testing, 10 docking trials were completed successfully, with the AMR reaching the docking pose and entering beneath the trolley without stopping due to obstacle alarms. These results indicate that the AI-assisted workflow improved under-ride carrier setup and accelerated problem identification and refinement, highlighting the potential of generative-AI tools to accelerate mechatronic system innovation.

1 Introduction

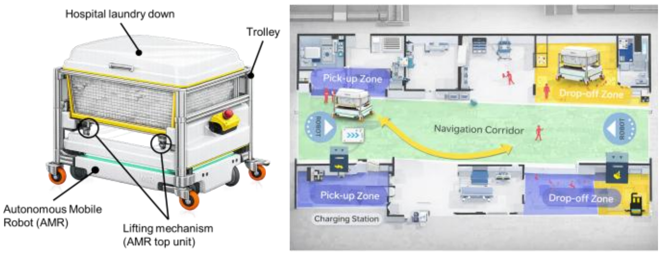
Recent advances in Generative Artificial Intelligence (Gen-AI) have reshaped engineers conceptualize, design, and optimize complex systems. Unlike traditional expert-driven CAD or simulation loops, generative-AI models particularly large language and multimodal models can autonomously propose design alternatives, infer performance constraints, and generate control or analysis code in response to textual prompts [1]-[3]. These capabilities enable engineers to move from descriptive design toward intent-driven workflows where the AI assists in requirement clarification, component synthesis, and automatic verification of design parameters [4]-[5].

Within industrial and system design domains, researchers have successfully applied Gen-AI to tasks ranging from mechanical optimization and additive-manufacturing part generation to process planning and quality-function deployment. Recent case studies demonstrate how GPT, Gemini or similar models can guide problem specification, generate morphological charts, or fine-tune CAD geometries through iterative goal, prompt, evaluate, iterate cycles [6]-[12]. Other works report AI-assisted adjustment of design variables in digital-twin environments [13], data-driven calibration of sensor networks [14], and generative parameter tuning in aerospace and manufacturing systems [15]-[17]. These studies utilized generative-AI not only accelerates ideation but also supports machine setup and evaluation, bridging the gap between conceptual reasoning and practical hardware realization [18], [19]. Few studies report physical prototypes where AI contributes directly to the configuration of sensors, and control logic. In automated logistics and mobile robotics fields demanding precise mechanical alignment and reliable feedback integration the application of Gen-AI remains largely unexplored. Autonomous Mobile Robots (AMRs), offer flexible navigation and payload transport, yet designing custom carrier modules require extensive mechanical iteration, sensor calibration, and control tuning to achieve dependable docking and lifting performance.

This work addresses that gap by presenting the Generative-AI-Assisted Implementation of an Under-Ride Lift Carrier for AMRs. Generative-AI was employed to synthesize design, setup issues for docking, lifting, transport operations, moreover problem-solving during setup and machine fine-tuning. The objective is to demonstrate how AI assistance can assist with setup time and improve accuracy in real mechatronic development within a validated prototype achieving 10 docking time successful trials were executed, which to reach the docking pose and complete the under-ride entry without stopping due to obstacle alarms

2. Methodology

The objective of this work was to design and fabricate an automated carrier prototype capable of transporting items between stations using an autonomous mobile robot (AMR) as the mobile base. The motivation arises from the continued reliance on manual transport devices, such as trolleys, cage carts, and roll carts, in offices, laboratories, and hospitals, where repeated handling increases labour demand, introduces ergonomic risk, and becomes inefficient in confined corridors or high-traffic areas. As illustrated in Figure 1(a), the proposed concept combines a wheeled trolley and a dedicated AMR top unit that performs under-ride docking and vertical lifting, allowing the robot to mechanically secure the trolley and carry the load as a single integrated system. The trolley is intended to hold service items such as hospital laundry, instruments, or consumables, while the lifting mechanism ensures stable transport without wheel caster drift during motion. Figure 1(b) summarizes the intended operational scenario in a hospital layout, where the AMR navigates along a predefined corridor to execute pick-up and drop-off tasks between service zones, with an intermediate charging station supporting continuous operation. From the design review, three principal carrier mechanisms were considered, towing, latching, and lifting, each with distinct trade-offs in mechanical complexity, spatial requirements, and payload stability. In this study, the under-ride lifting approach was selected because it supports precise docking, maintains a compact footprint, and avoids the swept-path penalty of towing in narrow environments such as elevators and corner turns. In addition, lifting reduces the dependence on caster behavior and floor friction, which can otherwise cause misalignment during approach and transport. Prior studies on mobile material handling report that vertical-lift or scissor-lift carriers can improve load stability, tolerate floor gaps, and reduce sensitivity to surface irregularities, enabling consistent operation under payload variation and uneven floor conditions [20]-[22]. This concept therefore provides a practical baseline for integrating sensors, control logic, and safety interlocks in later stages.



(a) (b)

Figure 1 Concept of AMR-carrier system
(a) AMR-carrier system component
(b) System operation

The hardware configuration of the prototype included of three main subsystems: (1) a mobile robotic or AMR base equipped with a differential-drive architecture, dual 200 W brushless DC motors, laser-based obstacle detection, and a rated payload of approximately 100 kg; (2) a custom upper-frame module, fabricated aluminum profiles, which supports the lifting platform and sensors, actuators, and control device; and (3) a detachable trolley prototype, constructed using lightweight aluminum framing and four swivel casters to simulate common transport carts. The robotic base provides autonomous navigation and localization through built-in lidar and ultrasonic sensors, while the upper-frame module serves as the mechanical and control interface for docking and lifting operations. The system architecture therefore integrates standard AMR navigation capabilities with a generative-AI-assisted co-design and set-up process, which supported concept synthesis, component parameterization, and mechanical adjustment in the following development stages. In this work, generative-AI as ChatGPT 5.2 (OpenAI) was incorporated as a design-assistant and issue solving to accelerate mechanical concept creation, component selection, and problem diagnosis throughout the system development process. The engineer interacted with a large language model (LLM) through structured prompts that described the project context, target performance, and hardware limitations. Each prompt response cycle produced design concepts, and control logic templates that were subsequently verified through human engineering judgment [9], [11]. During the mechanical design and specification screening phase, the AI model generated multiple structural configurations for the under-ride carrier, such as alternative scissor-lift linkages, actuator placement, and aluminum-profile arrangements. The engineer evaluated these suggestions for manufacturability and ease of assembly, then refined the suited candidate using CAD modeling. This co-design timeline was illustrated in Figure 2. By combining computational reasoning from AI with domain expertise, design iterations that previously required several days of trial-and-error could be completed within hours, consistent with time-saving effects reported in recent AI-assisted engineering studies [23]-[25].

Moreover, generative-AI also assisted in identifying issues and guiding fine adjustments during the integration stage. This human-in-the-loop workflow is illustrated in Figure 2 Human–AI co-design workflow with 6 steps:
1. Requirement definition → AI outputs candidate mechanisms & constraints.
2. Approach selection (lifting) → AI outputs pros/cons + dimension guidelines.
3. CAD parameterization → AI outputs param ranges, tolerances, assembly notes.
4. Sensor placement & docking marker guidance → AI outputs placement rules, failure modes.
5. Issue diagnosis (LiDAR/caster) → AI outputs hypotheses + modifications.
6. Validation planning → AI outputs trial protocol + metrics.

This workflow allowed the system to benefit from AI's, resulting in a design that met both functional and safety requirements. Overall, the generative-AI–assisted process significantly supported adaptive learning during prototype fabrication and testing. In summary This study also serves as a proof-of-concept trial to evaluate the accuracy and feasibility of under-ride docking on a prototype trolley, demonstrating the practical potential of the proposed lifting carrier system.

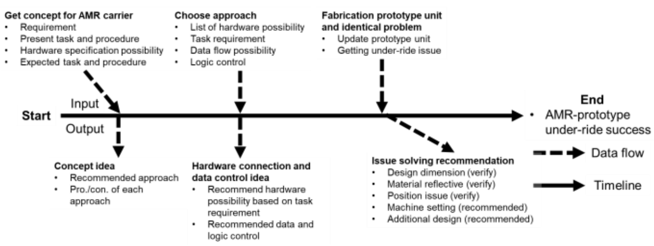


Figure 2 Key timeline of interactions between human participants and gen-AI assistance

In this study, generative-AI assistance was operationalized through structured prompt templates to ensure transparency and reproducibility of the co-design process. First, the engineering team prompted the AI to act as a machine and sensor design expert and to propose an under-ride trolley geometry for an AMR lift carrier.

The prompt explicitly required (i) a brief geometry concept and (ii) a parameter table describing the under-ride window, bar-guide dimensions and height, caster setback distance, frame member placement, safety margins, and tolerance notes, together with three key design risks and mitigations. The AI output suggested a rectangular trolley with a clear corridor aligned to the AMR centerline, a front bar-guide positioned at the LiDAR scan plane to strengthen docking detectability, and recessed casters to minimize sensor interference.

Second, when under-ride docking initially failed, a troubleshooting prompt was used to capture the observed failure mode: the AMR stopped before entering beneath the trolley due to an unclean edge in the LiDAR scan caused by the caster assemblies, leading the planner to classify the region as occupied.

The prompt required the AI to generate (a) root-cause hypotheses, (b) prioritized mechanical fixes, (c) prioritized docking-logic fixes, and (d) a verification checklist. In response, the AI identified likely causes such as reflective and angled caster brackets producing intermittent LiDAR returns at approximately 230 mm height, caster placement occluding the bar signature, insufficient retro-reflectivity of the bar, and non-square approach yaw. It then recommended actionable modifications, including moving casters rearward by 50–70 mm, adding a 40–60 mm retro-reflective strip with matte-black backing at the LiDAR plane, removing sharp protrusions near the scan plane, adding passive V-guides for self-centering, and using a precision docking sequence with reduced approach speed and a pre-dock pose aligned with the bar centerline. The verification checklist focused on confirming a continuous bright return from the bar in scanner view and successful repetition across multiple docking trials without early stop.

To evaluate the under-ride docking performance of the AMR–carrier prototype, we conducted a controlled docking experiment consisting of repeated trials before and after the AI-guided design update. The test area was a flat indoor floor with a clear approach corridor, and the trolley was placed at a fixed reference location marked on the floor to maintain consistent geometry across runs. The AMR started with a predefined pre-dock pose positioned approximately 1.0 m in front of the trolley, with the robot facing the trolley centerline. The docking mission was executed using the same approach speed and mission sequence for all trials within each condition. Two conditions were tested: (1) baseline design (before modification), and (2) updated design (after applying AI recommendations). For each condition, 10 docking trials were executed. A trial was considered successful if the AMR was able to reach the docking pose and complete the under-ride entry without stopping due to obstacle alarms. A trial was considered failed if the navigation stack stopped early (alarm state) or if the AMR could not enter the under-trolley corridor. In baseline condition, the AMR consistently stopped before reaching the docking pose because the front LiDAR interpreted caster assemblies as obstacles, resulting in an unclean edge and causing the local cost map to classify the under-trolley region as occupied. After the AI-guided update (caster repositioning and precision-docking activation near the guide bar), the same experiment was repeated for 10 trials to verify repeatability. Docking quality was evaluated using a binary outcome, defined as whether the AMR could successfully complete the under-ride docking manoeuvre. A trial was labelled successful if the AMR reached the intended docking pose and entered beneath the trolley without triggering obstacle alarms or early stopping. A trial was labelled failed if the AMR halted before the docking pose, entered an alarm state, or could not complete under-ride engagement. The results are therefore reported primarily as success rate (success/10) for each condition.

3 Results

The developed prototype represents the outcome of the generative-AI–assisted design applied to the under-ride lifting carrier concept. Figure 3 illustrates the complete mechanical assembly consisting of three primary components: the autonomous mobile robot (AMR) base, the custom upper frame, and the prototype trolley. The upper unit frame, fabricated from lightweight 60×30 (unit: mm) section aluminum extrusion profiles, was dimensioned according to the AMR's operational envelope and ground clearance parameters derived from the earlier design analysis.

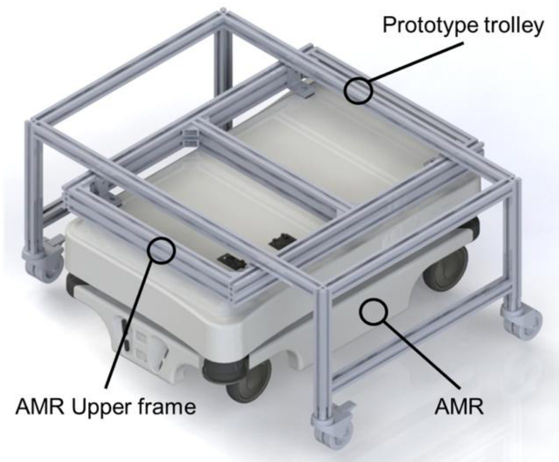


Figure 3 Overall structure component of AMR-carrier prototype

This structural module functions as an intermediary layer between the mobile platform and the detachable trolley, providing both mechanical rigidity and interfaces for future installation of sensors, lifting actuators, and control electronics. The frame geometry allows direct mechanical coupling with the AMR's payload surface through standardized mounting holes, ensuring structural stability while maintaining minimal added mass. The prototype trolley was designed to match the under-ride clearance of the AMR base, enabling smooth entry and alignment during docking. Four swivel casters were integrated to facilitate pre-positioning and to simulate real material-handling carts commonly used in logistics activity.

The trolley design detail component had been illustrated in Figure 4 incorporating the bar-guide structure that acts as the optical and mechanical docking reference for the AMR. The front crossbar 0.65 m in length and positioned approximately 230 mm above the floor defines the under-ride access window corresponding to the AMR's lidar scanning plane, while the overall width of 0.9 m provides sufficient clearance for lateral tolerance during approach. The guide bars were positioned to create a rigid rectangular frame that preserves parallelism and assists the robot's alignment upon entry. This configuration was selected through the early generative-AI–assisted concept evaluation, which identified the lifting approach as the most efficient solution in constrained environments.

The resulting prototype successfully demonstrates the relationship between the AMR upper frame and the trolley geometry, validating that the designed dimensions permit under-ride movement, and subsequent lifting without collision. This configuration forms the baseline for further integration of actuators and sensor feedback modules in subsequent development stages.

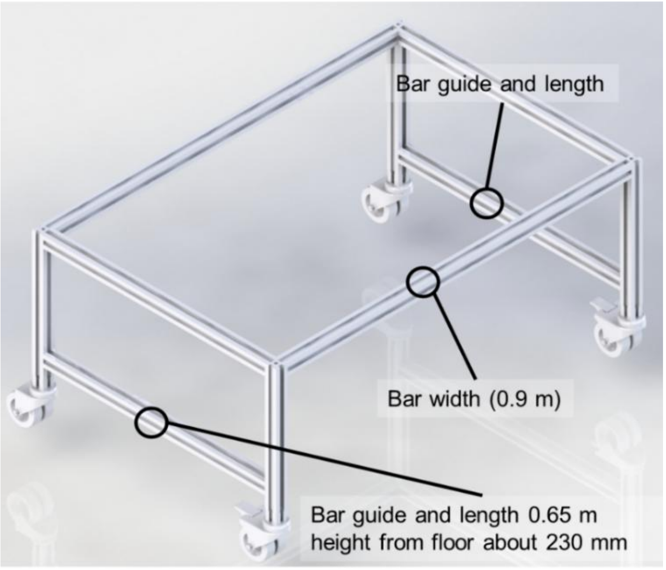
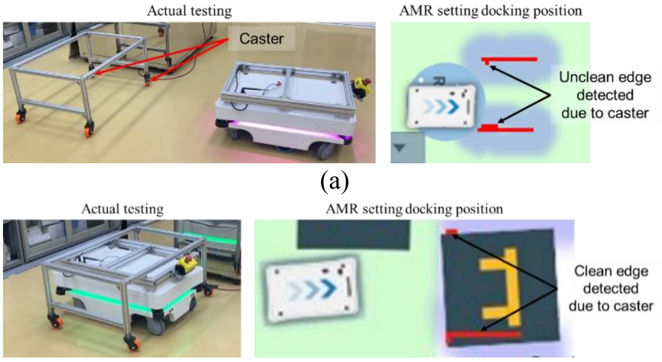


Figure 4 Overall structure of prototyping trolley

To evaluate the under-ride docking performance of the fabricated AMR–carrier prototype, we conducted 10 repeated docking trials in each trial under consistent nominal approach conditions, as summarized in Figure 5. The initial trial in Figure 5(a) highlights a representative docking failure (10/10 Rejected) that occurred when the AMR attempted to drive beneath the trolley. Although the carrier height and alignment were within the expected range, the robot did not advance to the intended docking pose. In this case, the front LiDAR mistakenly interpreted the trolley's caster assemblies as obstacles, producing an unclean edge in the scan and triggering conservative obstacle handling. Consequently, the navigation stack halted the robot before it reached the target docking pose (purple alarm state), and the under-ride maneuver could not be completed. Post-test inspection suggested that this failure was driven mainly by the caster brackets' reflectivity, geometry, and mounting position. In particular, sharp edges and highly reflective surfaces generated intermittent returns and small discontinuities at the LiDAR scan plane, located approximately 230 mm above the floor. These artifacts were then propagated into the local cost map, causing the onboard mapping and obstacle-classification module to mark the region beneath the trolley as occupied. As a result, the planner treated the under-trolley area as a blocked region rather than recognizing it as an open docking corridor, leading to an early stop before full under-ride engagement.



(a)

(b)

Figure 5 Under-ride testing of AMR-carrier prototype
(a) under-ride fails (docking undetectable)
(b) under-ride success (docking detectable)

To improve clarity, the AI co-design workflow used for issue solving is presented as a reproducible human–AI loop that links observation, prompt construction, engineering verification, and repeated validation. First, the team observed and logged the failure mode during under-ride docking, where the robot stopped early and the region beneath the trolley was classified as occupied due to an unclean edge in the LiDAR scan. Second, these observations were encoded into a structured prompt that included key sensor parameters (e.g., LiDAR scan-plane height), trolley geometry (frame and caster locations), and trial evidence (success/fail outcomes). Third, the generative-AI model produced ranked root-cause hypotheses and candidate corrective actions, separated into mechanical changes and docking-sequence logic updates. In this case, the AI identified caster-related scan interference as the dominant factor and recommended (1) repositioning the casters rearward to reduce overlap with the detection zone and (2) enabling a precision-docking mode when approaching the guide bar to improve robustness near the trolley boundary. Fourth, engineers screened these recommendations for feasibility and safety, implemented the selected modifications, and updated the docking mission accordingly. Finally, the configuration was re-tested using the same protocol to confirm repeatability for 10 docking trials were executed before the update (10/10 rejected) and 10 trials after applying the AI-guided changes (10/10 accepted), as shown in Figure 5. After the update, LiDAR returns exhibited a continuous, clean edge profile, allowing the robot to detect the docking target and complete under-ride entry without obstacle alarms. Overall, this combined workflow demonstrates how AI-assisted reasoning can accelerate diagnosis of sensor–mechanical interactions and support systematic parameter refinement for reliable machine setup.

In summary, the integration of generative artificial intelligence throughout the design and under-ride testing process significantly enhanced both the efficiency and precision of the prototype's development. The AI acted as a co-engineering partner, assisting in concept generation, component configuration, and rapid troubleshooting of mechanical and sensing issues.

4 Conclusion

This case-study presents a generative AI assisted implementation of an under-ride lift carrier for autonomous mobile robots. Through iterative collaboration between engineers and AI tools, the development process was noticeably accelerated from early concept to under-ride validation testing. The conclusion illustrates AI assistance can support system design and problem resolution in complex mechatronic development following:

1. AI-assisted fitter possibility and approach solution (towing, latching, lifting), allowing selection of the most feasible under-ride lifting approach based on spatial and operational constraints.

2. AI-assisted co-design process and supported human engineers in synthesizing structural geometry, sensor positioning, and control-logic through prompt-based analysis, reducing design iteration time.

3. AI-assisted issue solving able to diagnose and proposed solutions for obstacle-detection and alignment errors by analyzing sensor data and environmental parameters, able to 100% successful under-ride docking precisely after guided modifications.

Overall, this framework establishes a practical use case for future AI-assisted engineering workflows, where intelligent assistance can continuously refine machine design and support setup optimization in real industrial and robotic applications. In future work, the research team will focus on developing a fully functional mechanical lift unit integrated with feedback sensors and closed-loop control. Design optimization will strengthen the structure and improve actuator efficiency, while prototype refinement will enhance stability, safety, and serviceability for repeated operation. To verify lifting capability, we will perform a staged load test with incremental weights up to the designed target of 50-100 kg, and document clear pass/fail criteria, lift stability (no slip or tilt), and any observable deformation. The control logic and full-scale testing results will then be used to validate lifting accuracy, repeatability, and reliability, advancing the under-ride AMR carrier toward practical autonomous material-handling deployment.

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