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Humanoid Capabilities Navigator

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Content

1 Introduction: Motivation and Objectives

In recent years, interest in humanoid robots has increased significantly, driven by rapid advances in artificial intelligence, perception technologies, and actuation. At the same time, the shortage of skilled workers in many major industrial nations is forcing companies to explore new opportunities for productivity growth. As a result, humanoid robotic systems are increasingly perceived as a potential key technology for future industrial and logistics applications. In particular, companies operating their own production and intralogistics systems are approaching technology providers and research institutions with a central question: when can humanoid robots be deployed in real-world environments, and for which types of tasks is their use technically viable?

In parallel to this growing interest, many organizations have begun to take a proactive role. Early humanoid robot systems are being acquired, direct exchanges with original equipment manufacturers (OEMs) are initiated, and collaborations with research institutions are established in order to assess the technology's potential at an early stage. Despite this momentum, a comprehensive, structured, and application-oriented assessment of humanoid robots and their capabilities is still missing. In particular, there is currently no overarching framework that systematically links the present and future capability performance levels of humanoid robotic systems with concrete industrial and logistics use cases.

To address this gap, Fraunhofer IPA has developed the Humanoid Capabilities Navigator (HCN) for industrial and logistics applications, which is presented in this whitepaper.

The objective of the HCN is to provide transparency regarding the maturity of humanoid robotic systems' capabilities (independent from marketing-driven impressions) and to systematically relate their capabilities to potential application scenarios. Alongside considerations such as economic efficiency, service life, and maintenance aspects, it thus provides important support for decisions relating to humanoid robots. The HCN is designed to support multiple stakeholder groups. It supports potential users to assess to what extent specific tasks can already be, or may in the future be, performed by humanoid robots from a capability perspective. OEMs gain a structured understanding of the maturity level of the capabilities of their systems and can identify areas requiring further development. Companies, research institutions, and governmental organizations are supported in identifying existing white spots where additional research and development efforts are necessary. Furthermore, the framework enables a scientific and neutral comparison of different humanoid robotic systems and supports initial market assessments by linking technical capabilities with potential application domains and their economic relevance.

In order to provide a clear and consistent basis for the subsequent analysis, this work follows a specific definition of humanoid robots and humanoid robotic systems. As no universally accepted definition currently exists, the definition used here is aligned with previous work by the authors from the research project »KMUmanoid« which focused on possible application scenarios for small and medium-sized enterprises (SME or KMU in German). A humanoid robot is defined as a mobile robotic platform featuring a human-like upper body consisting of a torso and two arms. A human-like head is optional; however, the robot must be equipped with sensors that allow perception of its environment. The arms may be equipped with grippers, which can be designed either as classical robotic grippers or in an anthropomorphic, human-like form. Mobility may be realized through bipedal, wheeled, or tracked locomotion, and anthropomorphic walking and balancing capabilities can be provided if required. Humanoid robots are designed to perform human-like tasks in environments that were originally created for human workers. This makes them particularly interesting for being used in brownfield scenarios since the integration efforts should be low.

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Beyond the robot itself, this work explicitly considers humanoid robotic systems. A humanoid robotic system comprises the humanoid robot in combination with all additional hardware and software components required for safe, reliable, and task-specific operation. This includes, but is not limited to, specialized tools and end-effectors, computing and control software, power supply and communication infrastructure, human-machine interfaces, and safety mechanisms. Depending on the application, a humanoid robotic system may integrate external sensors, offboard computation resources, remote supervision or teleoperation capabilities, as well as workplace equipment such as fixtures, conveyors, machines, or production cells.

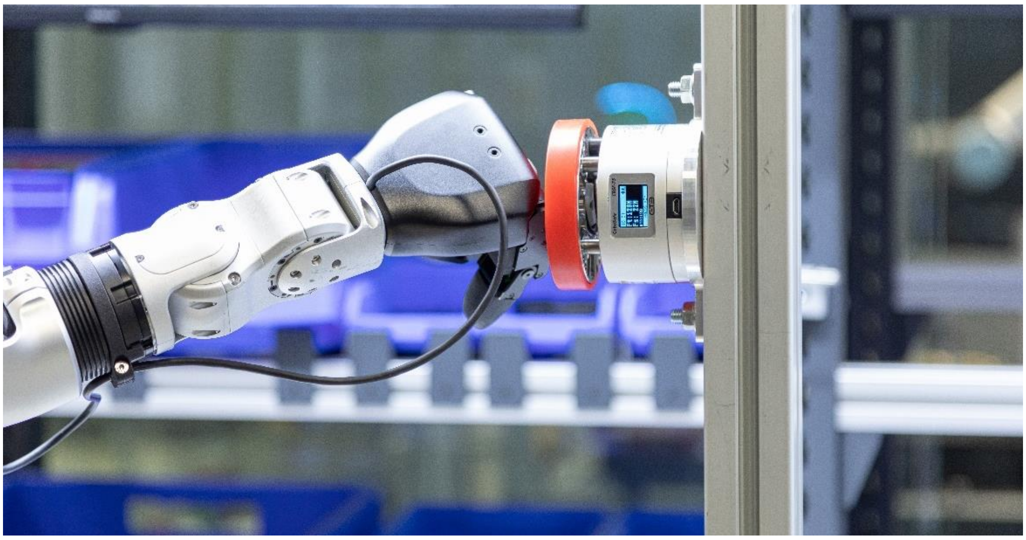
To make humanoid robotic systems deployable in real-world industrial environments, open and interoperable APIs are fundamental as they enable seamless integration with existing digital infrastructures and higher-level control systems. Given the current dynamic developments and constantly changing, vendor-specific system configurations, the presence and compatibility of such APIs must be examined separately for each robot model and manufacturer.

2 Capability Taxonomy for Humanoid Robots

2.1 Structure, Maturity Logic, and Application

The newly developed capability taxonomy structures the capabilities of humanoid robotic systems into four individual domains:

1. Mobility and Locomotion
2. Manipulation
3. Cognition
4. Safety and Security



These domains represent the core functional pillars of humanoid robots, especially in industrial, production, and logistics environments. The classification follows the technical system architecture and enables a differentiated assessment of domain-specific strengths and limitations.

Within each domain, individual capabilities are described using a discrete maturity scale ranging from Level 0 to Level 4. Level 0 represents the complete absence of a capability or a purely static, non-adaptive implementation that does not handle variability or uncertainty.

At the upper end of the scale, Level 4 describes highly autonomous, robust, and strongly generalized capabilities that operate reliably even under unknown, dynamic, or disturbed conditions.

Level 4 is thus defined as technically visionary and is comparable to human capabilities or even exceeds them. Levels 1 to 3 in between describe an increase in flexibility, stability and autonomy across the capabilities of the domains. Note that some capability levels might depend on the maturity of other capabilities. Take, for example, a high maturity of »Path Planning«, which requires a dynamic representation of the environment to be available and thus also a high maturity of »Localization & Mapping«. Still, each functionality needs to be assessed individually to estimate the usability of a humanoid system for certain use cases.

Progression along the maturity scales is not intended to represent linear performance improvements, but rather qualitative shifts toward increased autonomy, robustness, and the ability to cope with uncertainty. Higher maturity levels are therefore not inherently better or necessary. Many economically relevant industrial and logistics applications can already be realized at relatively low maturity levels, provided that these capabilities are reliable, reproducible, and safely integrated.

The taxonomy is applied in a use-case-driven manner. For a given industrial application, the required capabilities are first identified based on the process description, assumptions, and boundary conditions. The minimum maturity level required is specified for each relevant capability. If a summary of the domain assessment is desired, the maturity level required for an entire domain is derived from the highest maturity level required for its constituent capabilities. If, for example, several manipulation capabilities are sufficient at low maturity levels, but a single critical manipulation capability requires level 4, the manipulation domain as a whole is interpreted as requiring level 4 maturity. This aggregation logic reflects industrial reality, where a single insufficiently mature capability can limit the feasibility of an entire domain and, ultimately, the overall use case.

For developers of humanoid robotic systems, the taxonomy (see Fig. 1) serves as a structuring and communication tool. It enables systematic classification of existing capabilities, transparent representation of the development status, and targeted identification of capability gaps with respect to concrete industrial use cases.

For industrial users and potential adopters, the taxonomy provides a structured decision-making framework to assess the suitability of humanoid robots for specific applications. Rather than relying on abstract performance claims, system capabilities and use-case requirements can be compared along clearly defined domains and maturity levels.

Figure 1: Humanoid Capabilities

Domain	Capability		Maturity				
	Description	*Purpose*	*0*	*1*	*2*	*3*	*4*
Mobility & Locomotion	Localization & Mapping	Self-positioning	Absent	Coarse, unstable	Coarse, stable	Accurate, dynamic	High-precision, disturbance-robust
	Path Planning	Route selection	Absent	Static map	Limited dynamics	Highly dynamic	Unknown, changing
	Motion Execution	Motion execution	Static	Fixed path	Static adaption	Dynamic adaption	Unstable terrain
	Terrain Adaptability	Stability control	Flat ground	Slightly uneven	Moderately uneven	Steps & compliant	Unstructured terrain
	Dynamic Payload Compensation	Stability under load	None	Gravity (known)	Gravity & inertia (known)	Adaptive gravity	Adaptive gravity & inertia
	Object Co-Motion & Spatial Coordination	Safe transport	None	Rigid object	Single articulated	Articulated chain	Non-rigid physics
Manipulation	Force Perception	Sensitive grasping	None	Trigger-based	Force-reactive	Active exploration	Dynamic force sensing
	Grasp & Manipulation Planning	Grasp selection	None	Model-based	Model-free (isolated)	Model-free (cluttered)	Articulated/ deformable
	Manipulation Execution	Task execution	Hard-coded	Reacitve (single-modal)	Reactive (multimodal)	Autonomous (uncertainty)	Autonomous (dynamic)
	Robot-Robot-Coordination	Cooperative manipulation	None	Time-based	Reactive sync	Predictive cooperation	Joint multi-agent
	Articulated Object Interaction	System operation	None	Known mechanism	Parameter adaptation	Structural object model completion	Affordance inference
Cognition	Perception	Environmental context	Not required	Known static	Known dynamic	Unknown static	Unknown dynamic
	Task planning	Goal orchestration	None	Fixed goals	Predefined blocks	Autonomous sequencing	Fully autonomous
	Learning	Behavioral adaptation	None	Parameter tuning	Offline learning	Online adaptation (minor)	Online adaptation (major)
	Data Exchange	Shared data space	None/static	Unstructured logs	Stuctured logs	Digital shadow	Digital twin
	Human-Robot Coordination	Teamwork	None	Step-by-step	Assisted	Reactiv	Proactiv
Safety& Security	Security	System protection	None	Basic protection	Standard compliance	Proactive control	Trusted governance
	Human-Centered Safety	Safe collaboration	None	Manual stop	Contact stop	Speed & force limiting	Predictive avoidance

3 Capability Dimensions and Maturity Scales

The following section introduces the capability domains and individual capabilities that form the foundation of the taxonomy. For each capability, its functional scope is described, and a corresponding maturity scale is defined to enable consistent assessment and comparison across use cases and robotic systems.

3.1 Mobility & Locomotion

3.1.1 Localization and Mapping

Localization and mapping refer to the capability of a robot to estimate its own position and orientation within an environment, potentially while maintaining or updating a spatial representation of that environment. This capability provides the sensory foundation for navigation and situation-aware motion. Reliable localization is a prerequisite for path planning, obstacle avoidance, and safe operation in industrial and logistics environments, especially under changing or dynamic conditions.

The maturity of localization and mapping capabilities reflects increasing accuracy, stability, and robustness with respect to environmental dynamics and external disturbances:

Level 0	Absent: The robot operates without any explicit localization capability and has no knowledge of its spatial position.
Level 1	Coarse, unstable: Position estimates are approximate and inconsistent, exhibiting drift or loss of localization over time.
Level 2	Coarse, stable (static): Localization is stable under static or low-dynamic conditions, with limited update frequency and reduced robustness to change.
Level 3	Accurate, dynamic: The robot maintains accurate and stable localization in dynamic environments through continuous sensing and frequent state updates.
Level 4	High-precision, disturbance-robust: The robot achieves high-precision real-time localization even under significant disturbances, partial occlusions, or sensor degradation.

3.1.2 Path Planning

Path planning refers to the capability of a robot to compute feasible and efficient routes from a start to a target location while avoiding obstacles based on an internal representation of the environment. This capability enables reasoning about motion before execution and is essential for industrial and logistics environments where both known and unknown obstacles must be avoided and efficient routes must be determined under varying environmental conditions.

The maturity of path planning reflects the robot’s ability to handle increasing levels of environmental dynamics and uncertainty:

Level 0	Absent: The robot does not perform path planning and relies on externally predefined motion or remains stationary.
Level 1	Static map: Paths are computed using a static environment model without considering dynamic obstacles or changes.
Level 2	Limited dynamics: The robot accounts for dynamic obstacles in otherwise structured environments, enabling basic avoidance and local replanning.
Level 3	Highly dynamic: Path planning continuously adapts to highly dynamic environments with frequent obstacle motion and changing conditions.
Level 4	Unknown, changing: The robot plans and optimizes paths in unknown or continuously changing environments, dynamically adapting routes under uncertainty.

3.1.3 Motion Execution

Motion execution refers to the capability of a robot to physically carry out planned movements by generating and controlling motions in real time. This capability represents the action layer of mobility and enables robots to respond to environmental events during movement. Reliable motion execution is essential for safe and effective operation in industrial and logistics environments, particularly when obstacles, surface conditions, or disturbances are present.

The maturity of motion execution reflects the robot's ability to react to increasing levels of environmental variability and instability during movement:

Level 0	Static: The robot does not execute motion autonomously and remains stationary.
Level 1	Fixed path: The robot strictly follows predefined paths without deviation, independent of environmental changes (e.g., classical AGVs).
Level 2	Static adaptation: The robot adapts its motion to newly detected static obstacles, enabling limited reactive behavior.
Level 3	Dynamic adaptation: The robot continuously adapts its motion in response to dynamic obstacles and moving entities.
Level 4	Unstable terrain: The robot maintains reliable motion execution under unstable or challenging conditions, such as crowds, uneven ground, mud, or slippery surfaces.

3.1.4 Terrain Adaptability

Terrain adaptability refers to the capability of a robot to maintain balance and stability during motion while interacting with varying ground conditions and external disturbances. This capability prevents falls and enables reliable spatial movement in industrial and logistics environments where floor conditions may vary, including uneven surfaces, steps, compliant materials, or external perturbations.

The maturity of terrain adaptability reflects the robot's ability to remain stable under increasingly challenging ground conditions and disturbances:

Level 0	Flat ground: The robot maintains stability only on flat, even surfaces under controlled conditions.
Level 1	Slightly uneven: The robot remains stable on surfaces with minor irregularities or small height variations.
Level 2	Moderately uneven: The robot maintains balance on moderately uneven terrain, requiring active stability control.
Level 3	Steps and compliant surfaces: The robot remains stable when traversing steps, absorbing impacts, and moving on compliant or yielding ground.
Level 4	Unstructured terrain: The robot maintains stability in unstructured and highly variable terrain without prior assumptions about ground properties.

3.1.5 Dynamic Payload Compensation

Dynamic payload compensation refers to the capability of a robot to detect, estimate, or measure carried loads and actively compensate their weight, inertia, and changes in load distribution within its motion and balance control of the whole body. This capability prevents instability, tipping, or falls when objects are picked up or transported. It is essential for safe operation in industrial and logistics environments where payload properties may vary, change, or shift during motion.

The maturity of dynamic payload compensation reflects the robot’s ability to handle increasingly complex and uncertain load conditions:

Level 0	None: The robot does not compensate payload effects during motion or balance control.
Level 1	Gravity (known): The robot compensates gravitational effects of predefined, known payloads using hard-coded parameters.
Level 2	Gravity and inertia (known): The robot compensates both gravitational and inertial effects of known payloads based on fixed models.
Level 3	Adaptive gravity: The robot adaptively compensates gravitational effects based on measured or estimated payload parameters.
Level 4	Adaptive gravity and inertia: The robot dynamically compensates both gravitational and inertial effects of measured payloads, including changes in load distribution during motion.

3.1.6 Object Co-Motion and Spatial Coordination

Object co-motion and spatial coordination refer to the capability of a robot to account for the geometry, kinematics, and physical properties of carried or attached objects during motion planning and execution through an environment. This capability enables safe navigation when transporting bulky, elongated, articulated, or movable objects through buildings and constrained spaces. It is essential in industrial and logistics applications where objects such as carts, trolleys, long loads, or containers must be moved without collisions or loss of control.

The maturity of object co-motion and spatial coordination reflects the robot’s ability to reason about increasingly complex object structures and physical behaviors during transport:

Level 0	None: The robot does not consider carried or attached objects during motion planning or execution.
Level 1	Rigid object: The robot accounts for a static, rigid object shape for basic collision avoidance during motion.
Level 2	Single articulated: The robot considers a single articulated object, such as a cart, with limited kinematic coupling.
Level 3	Articulated chain: The robot accounts for kinematic chains of articulated objects, such as multiple connected carts, during navigation.
Level 4	Non-rigid physics: The robot considers physical properties of non-rigid or deformable objects, such as fluids or flexible loads, during motion planning and execution.

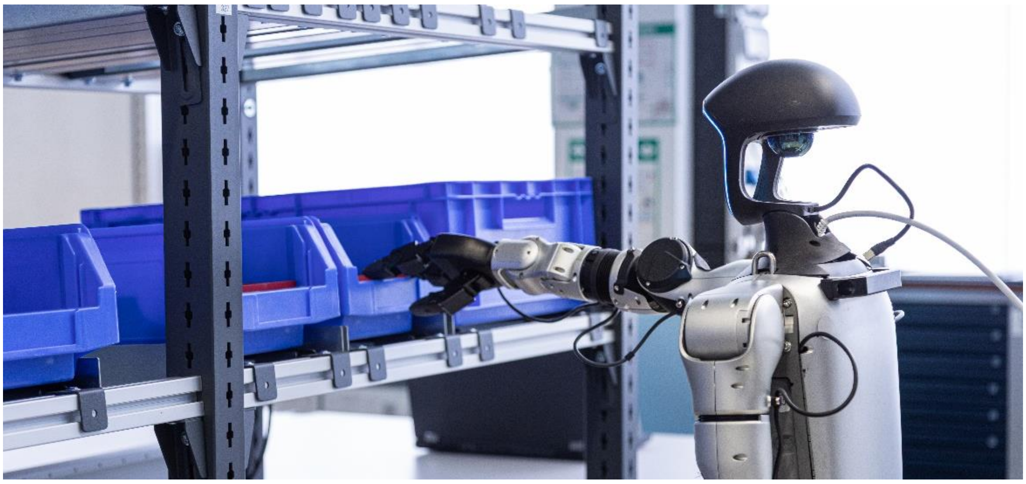
3.2 Manipulation

3.2.1 Force Perception

Force perception refers to the capability of a robot to sense and interpret contact forces, pressures, and surface-related interactions during physical interaction with objects or the environment. This capability enables safe and sensitive grasping by allowing the robot to adjust applied forces and avoid damage during contact. It is fundamental for fine manipulation tasks in industrial and logistics settings, particularly where handling fragile objects, precise assembly, or physical interaction with the environment are required.

The maturity of force perception reflects the robot’s ability to sense, interpret, and actively use force-related information during manipulation:

Level 0	None: The robot has no sensory feedback related to contact forces or pressure.
Level 1	Trigger-based: The robot detects simple contact events or thresholds, such as object grasped or resistance reached.
Level 2	Force-reactive: The robot reacts to measured forces during manipulation, enabling basic force-controlled tasks such as insertion or fitting.
Level 3	Active exploration: The robot actively uses force feedback to explore object properties, surface characteristics, or contact conditions.
Level 4	Dynamic force sensing: The robot perceives dynamic forces across contact interfaces, enabling continuous, high-resolution force feedback during complex manipulation.



3.2.2 Grasp and Manipulation Planning

Grasp and manipulation planning refers to the capability of a robot to perceive objects, determine suitable grasp points, and plan how objects should be grasped and used to fulfill a task. It is essential for handling tools, operating mechanisms such as door handles, and performing object-centric tasks in industrial and logistics environments.

The maturity of grasp and manipulation planning reflects increasing generality, robustness, and independence from predefined object models:

Level 0	The robot performs no grasp planning and simply moves toward the object center without considering a grasp strategy.
Level 1	Model-based: Grasp and manipulation strategies are planned using predefined object models known in advance.
Level 2	Model-free (isolated): The robot plans grasps without explicit object models in isolated, uncluttered environments.
Level 3	Model-free (cluttered): Grasp planning is performed in cluttered environments with multiple objects and occlusions.
Level 4	Articulated/deformable: The robot plans grasps and manipulation strategies for articulated or deformable objects, such as door handles, clothing, or flexible materials.

3.2.3 Manipulation Execution

Manipulation execution refers to the capability of a robot to physically carry out planned grasping and manipulation actions, including moving, placing, and holding objects at the workspace. This capability enables the realization of manipulation plans in the physical world. It is essential for performing object handling tasks reliably in industrial and logistics environments, where sensor uncertainty, environmental variability, and changing target conditions are common.

The maturity of manipulation execution reflects increasing autonomy, robustness, and adaptability during task execution:

Level 0	Hard-coded: The robot executes predefined, hard-coded trajectories without sensor-based feedback.
Level 1	Reactive (single-modal): The robot reacts to visual or haptic sensor input during execution, enabling basic reactive adjustments.
Level 2	Reactive (multimodal): The robot integrates multiple sensor modalities to reactively adjust manipulation during execution.
Level 3	Autonomous (uncertainty): The robot autonomously performs complex manipulation tasks despite sensor uncertainty or partial observability.
Level 4	Autonomous (dynamic): The robot executes complex manipulation tasks under dynamic changes in the environment and target location, adapting its actions in real time.

3.2.4 Robot-Robot Coordination

Robot-robot coordination refers to the capability of multiple robots to synchronize and coordinate their motions in order to perform shared manipulation tasks. This capability enables cooperative and reactive tasks that cannot be achieved by a single robot alone, such as handling large objects, synchronized assembly (e.g. for cables), or shared manipulation in industrial and logistics environments.

The maturity of robot-robot coordination reflects increasing levels of coupling, anticipation, and joint decision-making among robots:

Level 0	None: Robots operate independently without any form of coordination.
Level 1	Time-based: Coordination is achieved through predefined timing or trigger-based execution using a centralized or general planner.
Level 2	Reactive synchronization: Robots synchronize their actions reactively based on sensor feedback, enabling basic cooperative behavior.
Level 3	Predictive cooperation: Robots coordinate based on a shared task context, predicting partner actions while planning independently.
Level 4	Joint multi-agent: Robots jointly plan and adapt their actions as a multi-agent system, dynamically assigning roles and adjusting strategies in real time.

3.2.5 Articulated Object Interaction

Articulated object interaction refers to the capability of a robot to manipulate objects with movable or jointed components, such as doors, drawers, buttons, levers, or mechanical systems, in order to achieve a functional outcome. This capability enables robots to operate machines, access restricted areas, and use tools designed for human interaction. It is critical in industrial and logistics environments where interaction with articulated systems is required for access, operation, or task completion.

The maturity of articulated object interaction reflects increasing autonomy and generalization in handling systems with movable components:

Level 0	None: The robot is unable to manipulate articulated objects.
Level 1	Known mechanism: The robot operates a known articulated system using predefined trajectories and fixed interaction patterns.
Level 2	Parameter adaptation: The robot adapts parameters of a predefined system model based on observations, without changing the underlying structure of the model.
Level 3	Structural completion: The robot infers missing structural elements of a partially known articulated object from observations.
Level 4	Affordance inference: The robot infers affordances and kinematic properties of previously unseen articulated systems through interaction and exploration.

3.3 Cognition

3.3.1 Perception

Perception refers to the capability of a robot to sense and interpret target objects, humans, and environmental states through onboard sensors to form an internal representation of its surroundings. This capability provides contextual information required for planning, navigation, and interaction. In industrial and logistics environments, perception enables robots to understand what objects are present, how they change over time, and how humans and other agents behave in the environment.

The maturity of perception reflects increasing generality and robustness in handling unknown and dynamic elements of the environment:

Level 0	Not required: The robot operates without perception, relying entirely on predefined assumptions about the environment.
Level 1	Known static: The robot perceives known objects in static environments with no expected changes.
Level 2	Known dynamic: The robot perceives known objects that may move or change state over time.
Level 3	Unknown static: The robot perceives previously unseen objects in static environments.
Level 4	Unknown dynamic: The robot perceives unknown objects, humans, and environmental states in dynamic and continuously changing environments.

3.3.2 Task Planning

Task planning refers to the capability of a robot to plan, sequence, and select actions or skills in order to achieve goals and make decisions about task execution. This capability forms the foundation for autonomous goal pursuit and prioritization. In industrial and logistics environments, task planning enables robots to structure complex activities, adapt task execution, and coordinate capabilities in response to changing objectives or conditions.

The maturity of task planning reflects increasing autonomy in decision-making and action sequencing:

Level 0	None: The robot does not perform task planning and relies on direct, fixed control signals programmed at a low level.
Level 1	Fixed goals: The robot receives predefined target positions or goals executed in a fixed sequence by a controller that translates them into control signals.
Level 2	Predefined blocks: The robot executes abstract, predefined functional blocks (e.g., spiral search), which are manually composed into task sequences by a human.
Level 3	Autonomous sequencing: The robot autonomously composes task sequences from a set of predefined capabilities, with the resulting plan reviewed or approved by a human.
Level 4	Fully autonomous: The robot autonomously generates functional blocks and assembles complete task plans without human intervention.

3.3.3 Learning

Learning refers to the capability of a robot to improve or adapt its behavior based on experience, feedback, demonstration, or process knowledge. This capability enables robots to adjust their function blocks (perception, navigation, or manipulation) to new tasks, environments, objects, or conditions without manual reprogramming. In industrial and logistics contexts, learning supports robustness, continuous improvement, and reduced commissioning effort.

The maturity of learning reflects increasing autonomy and scope of behavioral adaptation:

Level 0	None: The robot executes a static program without any learning or adaptation.
Level 1	Parameter tuning: Contextual knowledge is used to adjust parameters of predefined skills without changing program structure.
Level 2	Offline learning: The robot learns a general-purpose model for a selected subtask offline, for example through supervised learning, and deploys it without further adaptation.
Level 3	Online adaptation (minor): The robot adapts its behavior online to handle minor changes in tasks or conditions during operation.
Level 4	Online adaptation (major): The robot performs significant online adaptations, modifying behavior or models to cope with major task or environmental changes.

3.3.4 Data Exchange

Data exchange refers to the capability of a robot to provide, synchronize, and share operational data within a common data space, enabling monitoring, analysis, and integration with external systems. This capability supports transparency, traceability, and governance by making robot data and task-related data (e.g., task status, object identifiers, or assigned target locations) accessible for supervision, diagnostics, optimization, and compliance. In industrial environments, data exchange is a prerequisite for monitoring system behavior, ensuring safety, and enabling digital representations such as digital shadows or twins.

The maturity of data exchange reflects increasing structure, timeliness, and bidirectionality of shared data:

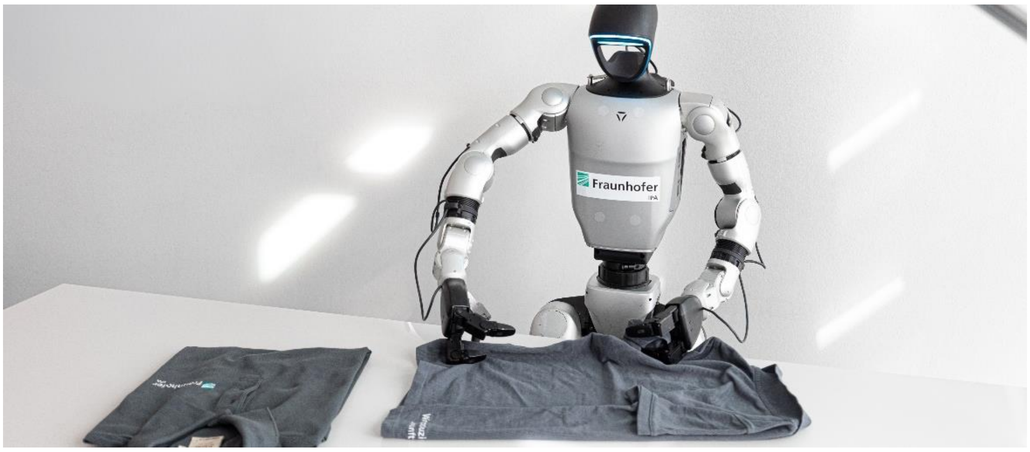
Level 0	None / static: No data exchange is available, or only static snapshots (e.g., static images) are provided.
Level 1	Unstructured logs: Unstructured log data is stored locally on the robot and synchronized only infrequently.
Level 2	Structured logs: Structured data is logged on the robot and synchronized in near real time with external systems.
Level 3	Digital shadow: A unidirectional, real-time digital representation of the robot state and task execution is maintained externally, allowing continuous monitoring of activities such as material flow, object placement, and process progress.
Level 4	Digital twin: A bidirectional, real-time digital twin enables continuous synchronization and interaction between the physical robot and its digital counterpart.

3.3.5 Human-Robot Coordination

Human-robot coordination refers to the capability of a robot to interpret human behavior, actions, or intentions and to respond in a cooperative manner during shared tasks. This capability enables effective teamwork between humans and robots in industrial and logistics environments. It supports safe, efficient, and intuitive collaboration by allowing robots to align their behavior with human actions, commands, or intentions.

The maturity of human-robot coordination reflects increasing levels of autonomy, anticipation, and cooperation

Level 0	None: No coordination is present; the robot follows a predefined, fixed execution sequence independent of human behavior.
Level 1	Step-by-step: The robot executes actions stepwise based on explicit commands issued by a human operator.
Level 2	Assisted: The robot proposes predefined actions or behaviors, which are explicitly confirmed by a human before execution.
Level 3	Reactive: The robot receives continuous commands, detects human movements, and reacts to them in real time.
Level 4	Proactive: The robot recognizes human intent and proactively adapts its behavior in anticipation of human actions.



3.4 Safety and Security

3.4.1 Human-Centered Safety

Human-centered safety refers to the capability of a robot to prevent harm to humans during interaction, ensuring safe behavior in shared workspaces by reacting to or anticipating potentially hazardous situations. This capability ensures safe human-robot collaboration across a wide range of use cases. It prevents hazardous outcomes, such as unintended collisions, excessive contact forces, or dropped objects during emergency stops and is tightly coupled with balance control, payload handling, and collaborative operation.

The maturity of human-centered safety reflects increasing levels of autonomy and anticipation in preventing hazardous situations:

Level 0	None: No safety mechanisms are present; the robot provides no protection for humans during operation.
Level 1	Manual stop: Safety relies on manual intervention only; safety stops occur exclusively via emergency stop buttons or mechanical shutdown.
Level 2	Contact stop: The robot detects physical contact or collision via sensors and actively stops after a contact occured.
Level 3	Speed and force limiting: The robot limits speed and applied forces when humans are detected nearby, enabling safe behavior during close proximity and collaboration.
Level 4	Predictive avoidance: The robot actively anticipates human movements and intentions, proactively adapting its behavior to avoid hazardous situations before they arise.

3.4.2 Security

Security refers to the capability of a robotic system to ensure that data and system states are handled in accordance with the intended use case and are protected against unauthorized access, unapproved modifications, and deliberate sabotage. This capability prevents data misuse, system manipulation, sabotage, and unintended changes during operation, remote access, trainings, configurations, or software update processes. In industrial and logistics environments, security is a prerequisite for trust, compliance, and safe long-term deployment of robotic systems.

The maturity of security reflects increasing levels of protection, governance, and trustworthiness across the entire data and system lifecycle:

Level 0	None: Neither data nor system changes are protected. Unauthorized access, manipulation, or sabotage may occur without detection.
Level 1	Basic protection: Basic security mechanisms such as password protection or simple access control are implemented, preventing trivial misuse or accidental changes but offering no protection against deliberate sabotage.
Level 2	Standard compliance: Security measures are formally defined and implemented, including logging, encryption, and access management. Unauthorized data access and system changes are systematically restricted, and sabotage attempts can be detected.
Level 3	Proactive control: Role-based access control and context-dependent authorization actively prevent unauthorized modifications or sabotage. Security processes continuously monitor data flows and system changes.
Level 4	Trusted governance: End-to-end protection ensures holistic control over the entire data and change lifecycle. Continuous compliance verification, tamper resistance, and full auditability enable proactive prevention of unauthorized changes and sabotage.

4 Mapping Use Case Requirements to Capabilities

The following section introduces a set of representative use cases selected from industrial and logistics environments to ground the capability taxonomy in concrete application scenarios and maps them to the HCN. The use cases have been chosen to cover a complexity spectrum of typical tasks in production, intralogistics, and maintenance, while remaining focused on realistic and economically relevant applications for humanoid robotic systems.

The use cases are as follows:

- Truck Loading / Unloading in Logistics Centers,
- Order Fulfillment / Picking
- Machine Tending
- Maintenance / Fundamental Service Tasks

Further details on the use cases, e.g. the overall goal, general challenges or key assumptions, can be found in the appendix.

The selected use cases were mapped to the HCN, based on their process descriptions, assumptions, system boundaries, and required functional skills. For each use case, minimum maturity levels were derived per capability domain following the aggregation logic described earlier. The resulting domain-level maturity requirements are summarized in Figure 2.

Truck Loading / Unloading requires a high degree of functional maturity across all domains. The use case is mapped to Mobility & Locomotion Level 3, reflecting the need for dynamic and accurate movement in constrained environments. Due to complex object handling and interaction with unstable loads, Manipulation is required at Level 4. The need for robust task coordination, perception, and data exchange leads to Cognition Level 4, while close human proximity and heavy payloads result in Safety & Security Level 4.

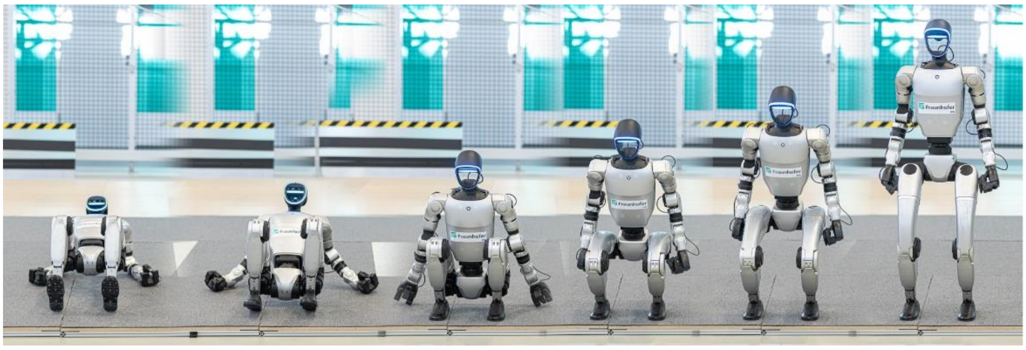
Order Fulfillment / Picking shows more moderate requirements. The structured warehouse environment leads to a Mobility & Locomotion requirement of Level 3, while standardized items and repetitive handling result in Manipulation Level 2. Task execution and system coordination can be achieved with Cognition Level 2, and shared workspaces with humans require Safety & Security Level 3.

Machine Tending is characterized by static and well-defined production environments. Consequently, Mobility & Locomotion Level 2 is sufficient. Handling of parts and interaction with machine interfaces require Manipulation Level 2, while predefined task sequences and limited environmental dynamics result in Cognition Level 2. Safety requirements are also mapped to Level 2.

Fundamental Maintenance Tasks combine structured environments with more complex physical interaction. Mobility requirements remain moderate at Level 2, while tool use and interaction with articulated machine components require Manipulation Level 3. Task execution and documentation needs lead to Cognition Level 2, and safety-critical interventions result in Safety & Security Level 3.

In summary, Figure 2 illustrates how different industrial and logistics use cases map to distinct domain-level maturity profiles. The results demonstrate that use-case feasibility is determined by domain-specific requirements rather than overall system performance, and that different applications stress different capability domains to varying degrees.

5 Case Study: Mapping an Existing Humanoid Robot to the Capability Taxonomy



To complement the use-case-driven requirement analysis, this section applies the taxonomy in reverse by mapping an existing humanoid robot system to the defined capability domains and maturity levels. In contrast to the previous chapters, which derived required maturity levels from application scenarios, this case study assesses the current capability maturity of a concrete humanoid robot system. The robot is mapped into the same capability taxonomy and visualization (see Figure 2) used for the industrial use cases, enabling a direct comparison between use-case requirements and the actual maturity profile of an existing system. This illustrates how the HCN can be used not only to analyze humanoid capabilities for applications, but also to transparently assess the limitations and development gaps of humanoid robotic systems with respect to industrial and logistics deployment.

One of the most famous robot manufacturers for humanoid robots is Unitree Robotics. Showcasing impressive walking and acrobatic skills, the humanoid robot G1 presents a view into the current state of the art when it comes to mobility. Many companies thus aim to identify possible use cases for this robot, but still not many real-world applications, aside from dancing shows or boxing competitions, can be seen. This stems mostly from the fact that the out-of-the-box system is basically an electronic device with multiple degrees of freedom and only the walking and stabilizing controllers are provided.

Some basic arm movement skills can be triggered, but more advanced features are not provided freely by the company. Similarly to when buying an industrial robot arm, actually programming a meaningful application is left to the system developers and integrators. Some open-source works provide a starting point for some basic functionalities like navigation but are still in heavy development and industrial-grade performance needs to be validated.

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GitHub, hugebot/ g1pilot

Figure 2: Mapping of Use Cases and Humanoid into the HCN

Domain	Capability: Description	Capability: Purpose	Maturity 0	Maturity 1	Maturity 2	Maturity 3	Maturity 4
Mobility & Locomotion	Localization & Mapping	Self-positioning	Absent	Coarse, unstable	Coarse, stable	Accurate, dynamic	High-precision, disturbance-robust
	Path Planning	Route selection	Absent	Static map	Limited dynamics	Highly dynamic	Unknown, changing
	Motion Execution	Motion execution	Static	Fixed path	Static adaption	Dynamic adaption	Unstable terrain
	Terrain Adaptability	Stability control	Flat ground	Slightly uneven	Moderately uneven	Steps & compliant	Unstructured terrain
	Dynamic Payload Compensation	Stability under load	None	Gravity (known)	Gravity & inertia (known)	Adaptive gravity	Adaptive gravity & inertia
	Object Co-Motion & Spatial Coordination	Safe transport	None	Rigid object	Single articulated	Articulated chain	Non-rigid physics
Manipulation	Force Perception	Sensitive grasping	None	Trigger-based	Force-reactive	Active exploration	Dynamic force sensing
	Grasp & Manipulation Planning	Grasp selection	None	Model-based	Model-free (isolated)	Model-free (cluttered)	Articulated/ deformable
	Manipulation Execution	Task execution	Hard-coded	Reacitve (single-modal)	Reactive (multimodal)	Autonomous (uncertainty)	Autonomous (dynamic)
	Robot-Robot-Coordination	Cooperative manipulation	None	Time-based	Reactive sync	Predictive cooperation	Joint multi-agent
	Articulated Object Interaction	System operation	None	Known mechanism	Parameter adaptation	Structural object model completion	Affordance inference
Cognition	Perception	Environmental context	Not required	Known static	Known dynamic	Unknown static	Unknown dynamic
	Task planning	Goal orchestration	None	Fixed goals	Predefined blocks	Autonomous sequencing	Fully autonomous
	Learning	Behavioral adaptation	None	Parameter tuning	Offline learning	Online adaptation (minor)	Online adaptation (major)
	Data Exchange	Shared data space	None/static	Unstructured logs	Stuctured logs	Digital shadow	Digital twin
	Human-Robot Coordination	Teamwork	None	Step-by-step	Assisted	Reactiv	Proactiv
Safety& Security	Security	System protection	None	Basic protection	Standard compliance	Proactive control	Trusted governance
	Human-Centered Safety	Safe collaboration	None	Manual stop	Contact stop	Speed & force limiting	Predictive avoidance

Unitree G1   Maintenance / Fundamental Service   Machine Tending   Order Fulfillment Picking   Truck/Container Unloading

6 Conclusion and Outlook

Interest in humanoid robots is surging, and current forecasts anticipate significant shipment growth over the next few years (see Figure 3).

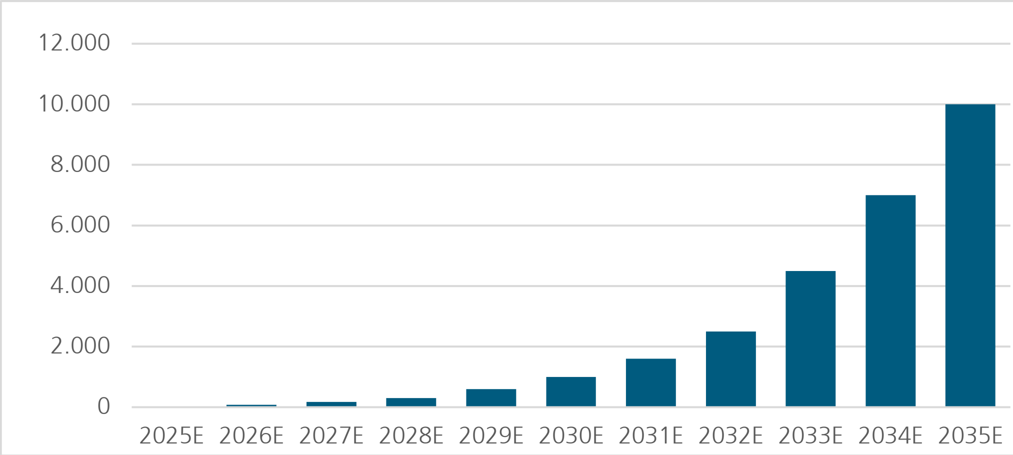

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Figure 3: Humanoid robot shipments; BofA Global Research estimates

To navigate this momentum, the presented HCN provides a structured, evidence-based way to assess existing humanoids, identify R&D needs, and calibrate market projections with real-world use cases based on a capability view. The HCN thus enables OEMs, system integrators, end users and research institutes alike to realistically assess the potential of today's humanoids and the humanoid capabilities required for specific applications.

In this paper, the industrial use cases Truck Loading/Unloading, Order Fulfillment/Picking, Machine Tending and Fundamental Maintenance Tasks were evaluated exemplary regarding required capabilities, whereas the taxonomy developed can be quickly transferred to other areas such as service or household. At the same time, based on the HCN, an existing humanoid was used as an example to compare its capabilities with these use cases. It was found that there are significant gaps between current humanoid capabilities and the capabilities required for real-world applications. Targeted research is needed to close these gaps, which are illustrated by way of example. Due to the rapid pace of technological development, it is difficult to predict when humanoids will reach which maturity level of the taxonomy developed.

Furthermore, the HCN makes it possible to better estimate market figures for humanoids. If reliable development speeds can be predicted with regard to maturity levels, clear development periods for specific applications and thus market potential can be derived.

As already mentioned in the introduction, the HCN should be understood as a valuable support tool for the use or further development of humanoid robots. It is important to understand that, especially for end users, other aspects besides the technical capabilities of humanoids must be evaluated when making a decision on their use, and that case-specific individual decisions are required.

These should include, for example, facts about the specific robot (range, payload, etc.), estimated availability (MTBF, service life, etc.), global service network and an economic analysis (CAPEX and OPEX). For further details, please refer to robotics experts and relevant publications, such as Fraunhofer IPA guides for economic efficiency and safety and Humanoid Benchmark activities.

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7 Fraunhofer IPA and Authors

7.1. Fraunhofer IPA

The Fraunhofer Institute for Manufacturing Engineering and Automation IPA, or Fraunhofer IPA for short, implements highly innovative and sustainable solutions in production engineering and automation, especially robotics, for a wide range of future-oriented industries. These can range from methods, components, and devices to complete machines and systems. The solutions are always linked to the institute's strategic cornerstones of "mass sustainability" and "mass personalization." The institute sees its main task as the transfer of knowledge, innovation, and technology from research results to applications to strengthen the competitiveness of companies. It sees itself as an independent partner that provides neutral advice and supports companies with project teams tailored precisely to their needs.

The automation division has been developing robot technologies for industry, commerce, and the service sector for more than 50 years. Over decades, this has included the development of core capabilities of mobile and service robots, which are also essential for humanoids. These include, for example, navigation, object recognition, path planning, and manipulation. Finally, the automation sector is widely networked at regional, national, and international levels and is active with several players in associations and committees. This enables the research work to be ideally embedded in strategic and regulatory measures.

7.2. Authors

Florian Jordan has been a Research Associate in the Department of Automation and Robotics since 2018. He specializes in segmentation of complex, unknown objects and physics-based simulation to plan grasping processes. Across several industry-near research projects, he has driven technology development and transfer to real-world applications.

Dr. Werner Kraus has been Senior Manager Research Unit »Automation and Robotics« at Fraunhofer IPA since 2019. He is an expert in cognitive robotics and machine learning, as well as their application in industry and the service sector. He has participated in several national and international research projects and is actively involved in the national and international robotics community through various positions and memberships.

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Franziska Mais was a Project Manager in the Strategy & Innovation domain at Fraunhofer IPA until 2026. She bridged strategic perspectives with technical capabilities in the field of automation and robotics. Her work focused on evaluating emerging technologies, assessing their industrial applicability, and translating technological potential into structured frameworks and decision support for industrial applications.

Alexander Renz has been a Research Associate in the Strategy & Innovation domain at Fraunhofer IPA since 2024. He combines strategic thinking with new technologies in industrial research. His work is centered on the evaluation of novel innovations, the assessment of their applicability, and the development of structured methods to translate technological opportunities into actionable strategies for progress.

Simon Schmidt has been Senior Manager of the Business Unit Automated Intralogistics, Manufacturing and Assembly Systems at Fraunhofer IPA since 2025. He also appears as a keynote speaker, particularly on the topics of automation and humanoids.

8 Appendix

8.1 Use Cases and Requirement Definition

The following section introduces a set of representative use cases selected from industrial and logistics environments to ground the capability taxonomy in concrete application scenarios. The use cases have been chosen to cover a complexity spectrum of typical tasks in production, intralogistics, and maintenance, while remaining focused on realistic and economically relevant applications for humanoid robotic systems.

Each use case is presented as a structured overview, including the overall goal, general challenges, a task-oriented process description, key assumptions, and system boundary conditions. In addition, high-level capability requirements are outlined for each use case, describing the required skills per functional domain without directly mapping them to specific maturity levels of the taxonomy. This classification ensures that use-case requirements are captured independently of the maturity assessment and can subsequently be mapped to the capability taxonomy of the HCN in a consistent and transparent manner.

Use Case 1 - Truck Loading / Unloading in Logistics Centers

Goal	1- Automated or semi-automated unloading of containers/trucks to reduce physically demanding work, stabilize process speed, and compensate for personnel shortages.
Process Description	1. Opening and securing the container and accessing it (Open doors, remove load securing, check work area for stability, obstacles, and hazards- 2. Inspecting the load (Structural assessment regarding: How are the boxes stacked? Which areas are accessible first? Are there damaged or unstable segments?) 3. Removing accessible boxes (Start at the front and progressively open deeper rows) 4. Securing, gripping, and removing boxes (Detach items individually or in pairs from the stack, ensure safe handling, place boxes at designated drop-off points) 5. Further clearing the area (Remove deeper layers and account for unforeseen conditions such as wet, deformed, or slipping boxes) 6. Final clearing (Check whether the container is completely empty, remove loose packaging materials, and document the unloading regarding irregularities, quantity, and damage.)

General Challenges	▪ Often uneven → Balance + foot sensing ▪ Deformable boxes → Adaptive gripping force ▪ Poorly lit → Multi-sensor perception ▪ Obstacles like chains/ropes or hooks inside the truck ▪ Interaction with humans optional ▪ Lifting 5–15 kg with whole-body coordination
Assumptions / Boundary Conditions	**Physical & Environmental Context:** ▪ Defined loading and unloading zones with a stable base layout ▪ Entry and exit from trucks at varying heights ▪ Packages may have shifted during transport **Object & Material Context** ▪ Packages of varying sizes and weights ▪ All packages are individually carryable ▪ Packages remain closed (no unpacking within the unloading area) ▪ No unpacking or repacking of packages within the robot working area **Human & Organizational Context** ▪ Humans and robots operate in the same workspace ▪ Trucks are opened by human workers ▪ Non-carryable items are handed over to human workers using auxiliary equipment **Process & Operational Assumptions** ▪ Loading and unloading follow a defined operational sequence **System Boundary Assumptions** ▪ Packages are placed at predefined handover or drop-off locations ▪ Task status or handover completion is communicated to downstream processes

Use Case 2 - Order Fulfillment / Picking

Goal	Automated or semi-automated picking of items from storage locations in logistics or fulfillment centers to reduce manual effort, stabilize throughput, and increase flexibility in handling mixed product assortments.
Process Description	1. Receive and understand the picking order (Retrieve the order from the WMS and identify items, locations, and quantities) 2. Navigate to the required storage location (Move through aisles and storage areas while avoiding obstacles and dynamic traffic) 3. Identify the correct item at the shelf (Verify item type via visual identification or barcode and locate the correct storage position) 4. Pick the item from the shelf or bin (Grip, remove, and safely handle the item without causing damage or mispicks) 5. Place the item into the designated order container (Deposit the item correctly and manage multiple order streams if applicable) 6. Deliver the consolidated items to the next process step (Transfer items to packing, AMRs, or conveyors and document order completion in the WMS)
General Challenges	▪ Narrow storage aisles → precise movement ▪ Adaptable, careful handling of shelf and objects ▪ Different shelf heights → reaching and accessing items from low to overhead levels ▪ Mixed lighting and visual complexity → reliable item identification ▪ Frequent human presence in aisles → safe operation around personnel ▪ Integration with WMS
Assumptions / Boundary Conditions	**Physical & Environmental Context:** ▪ Mixed lighting and visual complexity → reliable item identification ▪ Frequent human presence in aisles → safe operation around personnel ▪ Integration with WMS **Object & Material Context** ▪ Items of varying size and shape ▪ Items are lightweight and individually pickable ▪ Items are stored in known locations ▪ Items are handled individually (no bulk picking)

Assumptions / Boundary Conditions

Process & Operational Assumptions

- Orders consist of multiple individual items
- Items are picked from shelves or bins
- Picked items are placed into designated order containers
- Orders are processed sequentially

System Boundary Assumptions

- An order management or warehouse management system provides picking tasks
- Target containers or drop-off locations are predefined
- Packing, consolidation, and shipping are handled outside the robot task

Use Case 3 – Machine Tending

Goal

Automated or semi-automated loading and unloading of production machines (e.g., CNC, injection molding, presses) to reduce repetitive manual tasks, stabilize cycle times and increase uptime, and increase flexibility in mixed-model production environments.

Process Description

1. Prepare and verify the machine task (Check machine status, retrieve job information, confirm that the machine is ready for loading)
2. Retrieve the part or material for processing (Pick up raw components, blanks, or semi-finished parts from supply racks, bins, or AMRs)
3. Load the part into the machine (Open safety doors if required, position the part accurately, secure it inside the fixture or loading area)
4. Start or confirm the machine cycle (Close machine doors, activate the cycle start command, monitor for immediate errors)
5. Unload the processed part after the cycle (Remove finished parts, visually check for defects, place them in designated trays or conveyors)
6. Handle exceptions and document activity (Report machine faults, missing parts, misalignment, or abnormalities; document completion in the production system)

- Mixed accessibility around machines → requires flexible positioning and maneuvering
- Precise placement of parts → accurate alignment for loading operations
- Adaptable gripping and stable carring

General Challenges	▪ Human presence in adjacent workstations → safe coexistence and predictable motion ▪ Cycle-time pressure → consistent, repeatable task execution ▪ Heavy parts far from CoG of robot → balance
Assumptions / Boundary Conditions	**Physical & Environmental Context:** ▪ Medium-sized CNC machines in a production hall environment ▪ Robot must lean into the machine workspace to load and unload parts **Object & Material Context** ▪ Aluminum parts and raw blanks ▪ Parts / blanks up to 5 kg ▪ Parts / blanks are known in advance ▪ Parts / blanks can be placed in an ordered manner on a flat surface o Finished parts do not change regularly (continuous production) **Human & Organizational Context** ▪ Robot operates autonomously ▪ No human enters the robot's working area ▪ Humans may move between machines ▪ Reordering of raw blanks and removal of finished parts is organized externally ▪ An order management system is available to coordinate tasks between robots **Process & Operational Assumptions** ▪ Robot loads and unloads a CNC machine for manufacturing aluminum parts ▪ One robot tends multiple CNC machines ▪ Robot performs visual inspection for manufacturing defects after unloading ▪ Robot performs rough cleaning of finished parts using compressed air before removal **System Boundary Assumptions** ▪ CNC machine type is known and set up ▪ CNC machine is not digitally connected ▪ Machine operation via physical buttons, screen, and status LEDs ▪ No automatic machine door

Use Case 4 – Maintenance / Fundamental Service Tasks

Goal	Automated or semi-automated execution of basic maintenance tasks - such as resetting equipment, performing simple checks, and handling routine service activities - to reduce technician workload, minimize downtime, and ensure stable plant operation.
Process Description	1. Receive and understand the maintenance task (Retrieve task information from the maintenance system and verify the affected equipment) 2. Access the designated machine or area (Move through the facility, navigate around obstacles, and position at the equipment requiring attention) 3. Perform visual and functional checks (Inspect indicators, displays, connectors, leaks, or abnormal noise; confirm status indicators) 4. Execute the required maintenance action (Pressing reset buttons, flipping switches, tightening simple connections, opening small access panels, replacing easily accessible parts) 5. Validate successful completion (Check whether equipment returns to normal operation; confirm status lights, messages, or motion) 6. Document the intervention and report findings (Record completion, abnormalities, or required follow-up actions in the maintenance/CMMS system)
General Challenges	▪ Varied machine layouts → flexible positioning and reach required ▪ Human-designed interfaces (buttons, levers, panels) → ability to interact with standard equipment controls ▪ Need for accurate visual inspection → reliable interpretation of lights, gauges, or displays ▪ Safe Coexistence and predictable movement ▪ Handling of complex objects (e.g. fluids refilling)

Assumptions / Boundary Conditions

Physical & Environmental Context:

- Industrial production hall environment
- Machines accessible from the shop floor
- Maintenance points reachable without dismantling equipment
- Limited but sufficient space around machines

Object & Material Context

- Small tools, containers, and consumables (e.g. oil, filters)
- Components and interfaces are known and standardized
- Objects are lightweight and manually handleable

Human & Organizational Context

- Robot operates autonomously during maintenance tasks
- Human technicians are present in the facility but not directly involved
- Maintenance tasks are predefined and scheduled
- Escalation to human technician possible if task cannot be completed

Process & Operational Assumptions

- Basic maintenance tasks (e.g. refilling oil, pressing reset buttons, visual checks)
- Tasks follow a fixed, step-based procedure
- Tasks are performed periodically or on demand
- No complex fault diagnosis required

System Boundary Assumptions

- Maintenance tasks are provided via a maintenance or task management system
- Machines may not be digitally connected
- Feedback is limited to task completion or failure
- Documentation of performed tasks is required

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