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# From Manual to Fully Autonomous MRI: A Structured Framework for Automation Levels

**J. Wohlers[1*], G. Wigger[1], M. Keil[1], M. Braun[1]**

[1] *Siemens Healthineers AG, Erlangen, Germany*
[*] *Corresponding author, julian.wohlers@siemens-healthineers.com*

*Abstract:. This work introduces a taxonomy for automation in MRI, adapted from vehicle automation standards. It defines autonomy levels, clarifying roles for humans and machines. The framework helps benchmark technology, guides clinical integration, and highlights challenges like system interoperability and legal responsibility as automation increases.*



## I. Introduction

The convergence of artificial intelligence (AI), automation, and robotics is rapidly transforming diagnostic imaging. While computer-aided detection and reporting are now established, the next frontier is the automation of the entire imaging workflow. However, the absence of a unified framework to describe autonomy of these systems impedes both technological progress & clinical adoption. This work introduces a taxonomy for levels of autonomy in diagnostic imaging, with a focus on MRI, to guide research, development, and regulatory efforts in this evolving field.

## II. Material and methods

To structure the progression of automation in diagnostic imaging, we adapted the SAE J3016 vehicle automation levels to the medical domain.

An adaption of this is necessary to consider the different circumstances. Firstly, the SAE J3016 does not differentiate different user groups. Mostly, autonomous vehicles are perceived as consumer goods used by non-professionals, while autonomous imaging systems are operated by trained professionals.
Another key distinction is the nature of the outcome. In autonomous imaging, the professional user is responsible for creating a product—the diagnostic images—which must meet clinical standards. The imaging process is not just about operating equipment, but about producing data that supports patient care. In contrast, autonomous vehicles are designed to achieve safe transportation from point A to point B rather than the creation of a product. A key difference to autonomous driving is also the absence of a "dilemma" situation. These differences further influence the design, oversight, and safety requirements of automation in each field. Our taxonomy distinguishes:

Hardware/Patient Handling Autonomy: Automation of patient positioning, coil placement, and contrast injection.

Software/Scanning Autonomy: Automation of protocol selection, image acquisition, reconstruction, quality control.

We define six discrete levels (0–5) of imaging automation, each characterized by the allocation of roles between the human operator and the automation system, as well as the system's fallback capabilities..

### II.I. Level of Autonomy

Our framework maps SAE vehicle automation levels to MRI workflow equivalents and technologist roles:

Level 0 (No Automation): Manual end-to-end workflow; the technologist is responsible for all aspects of patient handling, planning, acquisition, and quality control.

Level 1 (Assistance): Guided setup assistance (e.g., table presets, laser alignment); the technologist operates the workflow while activating assist features.

Level 2 (Partial Automation): Protocol standardization and auto-parameterization (e.g., auto-slice planning, auto-coil detection); the trained healthcare professional curates automation outputs and approves system suggestions.

Level 3 (Conditional Automation): Autonomous acquisition for routine exams with real-time IQ guardrails; the technologist supervises automation, monitors alerts, and resolves artifacts. Staff and machine work as a team.

Level 4 (High Automation): End-to-end autonomous routine workflow; the technologist's role shifts to exception and orchestration, with minimal manual intervention. Staff is mostly only observing.

Level 5 (Full Automation): Fully autonomous MR within defined indications, including robotic patient handling and automated reporting; the technologist provides oversight and governance.

### II.I. Transitions

Transitions between autonomy levels involve distinct shifts in focus, core responsibilities, automation handoff, competencies, and safety practices:

L0→L1: From manual execution to tool-assisted setup; technologist activates assists and maintains manual positioning.

L1→L2: From tool use to curation of automation outputs; technologist reviews/overrides auto-planning & manages coils.

L2→L3: From parameter setting to supervision of autonomous acquisition; technologist monitors alerts and intervenes for artifacts.

L3→L4: From supervision to exception management; technologist handles rare cases and validates quality gates.

L4→L5: From exception management to oversight/ governance; technologist assumes operator-of-record duties and safety.

### Example

Patient is centrally registered, and the system suggests an exam protocol based on existing patient information (level 3). The technologist must confirm the selected scan procedure based on the latest patient information during preparation (level 3). The technologist then positions the patient (level 2). The selected scan procedure is initiated by the technologist, and the scanning process is carried out fully autonomously by the scan software (level 4). The technologist only needs to intervene in the event of a patient interruption (level 4).

## III. Results and discussion

Applying this taxonomy to MRI reveals distinct bottlenecks and opportunities:

Software autonomy is advancing rapidly, with AI-driven protocol optimization, automated reconstruction, and quality control nearing full automation in some prototypes.

Hardware autonomy—particularly in patient handling—remains a major challenge, limiting the achievable level of end-to-end automation.

Our framework allows for mixed autonomy levels. For example, a clinical site may implement Level 4 scanning autonomy (highly automated acquisition and Quality Control) while maintaining Level 2 Hardware/Patient Autonomy (AI-assisted patient positioning). This multi-axis approach provides a more nuanced and actionable roadmap than single-axis models such as the Levels of Autonomous Radiology (LoAR).

It is important to clearly understand the responsibilities that come with a certain level of autonomy. The challenge is that levels of autonomy can differ according to the step in the workflow.

This has regulatory implications since today, some applications require clearance from the technologist, and the question will be whether that can shift to the machine.

On another level, the user also must trust the system in order to accept it. Trust is established when results are consistent, reproducible, and meet the operator's precise requirements. Therefore, the configurability of automation is crucial for building user trust.

The proposed taxonomy clarifies the current state and future trajectory of automation. It supports:

Technology developers in benchmarking and communicating system capabilities and limitations.

Clinicians and administrators in understanding workflow implications and safety considerations.

All stakeholders including regulators in developing standards and guidelines for safe and effective deployment.

Other modalities may be using a similar taxonomy, though it is important to point to the subtle differences. Thus, other modalities may run autonomously on different levels for other parts of the workflow process.

The implications for product development are wide: from technical risk mitigation to usability questions. Technically preventing errors in the interaction with autonomous products as well as making sure that this interaction is well understood. It will be crucial to design for all aspects of User Experience to get acceptance of all involved user groups and stakeholders. Furthermore, patients are involved who need to accept and understand increased autonomy as well.

In imaging, the workflow does not demand split-second reactions to emergencies. This contrasts with domains where immediate human intervention is critical for safety, such as in autonomous driving or surgical robotics. As a result, safety protocols in autonomous imaging focus more on robust fallback mechanisms and clear oversight responsibilities, rather than on instant manual overrides

## IV. Conclusions

A structured taxonomy is essential for advancing safe, effective, and trustworthy automation in diagnostic imaging. Our framework provides a clear foundation for interdisciplinary collaboration and innovation in medical robotics and AI. The current regulatory framework for medical devices should be extended by a dedicated set of requirements. It is proposed to specify the dedicated risks of autonomous scanning with an MR system and, where possible, to formulate proposals for measures to mitigate these risks. A distinction should be made between manufacturers on the one hand and operators and users on the other. It seems beneficial to develop a standard for each of these two groups.

### Author's statement

All authors are employees of Siemens Healthineers AG.

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