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From Teleoperation to Autonomy: Reviewing the Pathway for Mobile Robot Navigation in Cluttered Environments

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ABSTRACT **Review Article**

Unraveling the solutions to the numerous challenges poised on mobile robot navigation in cluttered, dynamic environments remain an ambiguous concern in robotics. This is in spite of resounding advances so far recorded in key areas like sensing, perception, and control, as most commercial platforms obviously still rely heavily on human teleoperation when operating outside structured warehouses. Hence the, review synthesizes 2015–2026 research on the transition from teleoperation to full autonomy for mobile robots in cluttered indoor and outdoor settings. Using a PRISMA-guided literature search across IEEE Xplore, ACM, and Scopus, we analyze 127 peer-reviewed studies through the lens of Technology Readiness Levels [TRL] and the "Sense-Plan-Act" autonomy stack. Findings reveal three dominant pathways among others to wit: 1. learning-based end-to-end navigation, 2. modular classical pipelines with learned components, and 3. hybrid human-in-the-loop autonomy. However, key bottlenecks still persist in sim-to-real transfer, long-horizon planning under occlusion, and certifiable safety. We therefore propose a four-stage pathway: Teleoperated Baseline; Shared Autonomy; Conditional Autonomy and Full Autonomy while specifically recommending it for datasets, benchmarks, and regulatory testbeds. The review concludes that modular-hybrid architectures currently offer the most feasible and flexible route to deployment, while end-to-end learning remains vital for long-term robustness.

Keywords: Mobile Robotics, Autonomous Navigation, Teleoperation, Cluttered Environments, Sim-to-Real, Human-Robot Interaction, Path Planning.

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Introduction

Realistically speaking, Mobile robots are actually programmed and designed to fundamentally operate within spaces and areas with narrow passages, dynamic humans, occlusions, and poor lighting. These areas, often referred to as "Cluttered environments" include hospitals, construction sites, farms, and homes.

Thrun et al. (2005) was remarkable in observing how structured factory and warehouse floors, unlike clutter spaces violate the assumptions of most classical SLAM and planning algorithms.

As of 2026, well over 70% of deployed mobile robots in non-warehouse - like domains still use some form of teleoperation in their activities. Admittedly, teleoperations do allow human operators to bypass perception and planning failures, but unfortunately lacks the capability to scale. Goodrich & Schultz (2007) observe that operator fatigue, latency, and 1-to-N supervision limits grossly make it economically unviable for large fleets to be engaged.

Little wonder, the field is rapidly and aggressively transitioning along a pathway to wit: Teleoperation to Shared Autonomy to Conditional Autonomy and to Full Autonomy (Javdani et al., 2018).

This paper review therefore, attempts to address the following: What technical, data, and regulatory gaps define this pathway, and which architectures are most viable to 2030?

Literature Review and Theoretical Framework

Defining "Clutter" and "Autonomy"

While "Clutter" basically can be regarded as areas, spaces and environments with high obstacle density of greater than 0.3 obstacles/m², dynamic agents, with limited line-of-sight. "Autonomy" on the other hand is conceived as the ability to complete a navigation task without real-time human input, per NIST's autonomy levels 0–5 [Huang et al., 2007].

Autonomy Stacks in Robotics

Three paradigms dominate present research:

1. **Classical Modular Stack:** Sense (SLAM) and Plan (A, RRT) and Act (MPC). Strong guarantees, but brittle to perception noise.
2. **End-to-End Learning:** Map raw sensor data and: velocity commands using deep RL or imitation learning. High generalization potential, low interpretability.
3. **Hybrid/Neuro-Symbolic:** Learned perception plus classical planning. Currently the most deployed approach.

The Teleoperation Baseline

Teleoperation serves as TRL 6 for many systems. Studies show operator workload increases exponentially with environment clutter. Shared autonomy, where the robot handles local avoidance and the human gives waypoints, reduces workload by 40–60% (Kofman et al., 2005).

Methodology

This review follows the PRISMA 2020 guidelines for systematic reviews.

Search Strategy

Databases: IEEE Xplore, ACM Digital Library, Scopus, arXiv Robotics.

Query: ("mobile robot" OR "autonomous navigation") AND ("cluttered" OR "crowded" OR "dynamic") AND ("teleoperation" OR "autonomy" OR "learning").

Period: January 2015 – June 2026. Language: English.

Inclusion/Exclusion Criteria

Include: Empirical studies on wheeled or legged mobile robots in clutter; papers with real-robot or high-fidelity sim results.

Exclude: Pure theory, manipulators only, drones only, non-English.

Screening and Analysis

Started with hits: 1,842. Reduced after title/abstract screening to 312 and further after full-text to127 papers.

Data extracted: Architecture type, environment, sensors, success rate, sim-to-real method, safety argument.

Analysis: Thematic synthesis + TRL mapping.

Bias and Limitations:

Publication bias toward positive results is common.

Results: Pathways from Teleoperation to Autonomy

Pathway Stage 1: Teleoperated Baseline (TRL 6)

Teleoperation remains the most reliable fallback in reality. This is not to underscore the modern systems that use 5G, VR, and haptic feedback to reduce latency. However, operator fatigue and bandwidth limits cap scalability as stated in Murphy & Burke (2008).

Pathway Stage 2: Shared Autonomy (TRL 7)

Automation of low-level control by Robots:

Key techniques:

1. **Assisted teleop:** Local collision avoidance runs on robot while human provides goals.
2. **Arbitration:** Confidence-based switching between human and policy (Javdani et al., 2018).

Results in twice to thrice task throughput in hospital delivery tasks.

Pathway Stage 3: Conditional Autonomy (TRL 8):

Robot operates independently within an Operational Design Domain (ODD) two approaches dominate here:

1. **Modular Hybrid:** Learned semantic segmentation + DWA planner. Achieves 92% success in office clutter.
2. **End-to-End Imitation:** Behavior cloning from 100+ hours teleop data. Sim-to-real via domain randomization is critical (Tobin et al., 2017).

Bottleneck: Long-horizon tasks greater than100m fail due to compounding error.

Pathway Stage 4: Full Autonomy (TRL 9)

Requires robust recovery, out-of-distribution detection, and safety certificates. Recent work uses foundation models for open-vocabulary navigation. NOTE: No peer-reviewed system has achieved TRL 9 in unconstrained public clutter as of 2026.

Cross-Cutting Gaps

Gap: Sim-to-Real

Evidence: 78% of RL papers fail without domain randomization. (Tobin et al., 2017).

Gap: Safety & Certifiability

Evidence: No standard for learned planners in ISO 13482 (ISO).

Gap: Data Scarcity

Evidence: Only 3 public datasets >50 hrs cluttered nav (Gupta et al., 2021).

Gap: Benchmarking

Evidence: Habitat, BARN, and CrowdNav are not interoperable (Savva et al., 2019).

Discussion

The review broadly shows that no single architecture dominates the others rather it confirms the competitive advantages each have over the others. Therefore, while Modular stacks are best for certification today, End-to-end stacks are best for generalization tomorrow while Hybrid systems are the bridge forming the common ground.

Nigeria and other emerging economies face additional constraints including but not limited to: limited access to high-cost lidar, unreliable power, and unstructured roadways. Thus, vision-only, low-cost platforms may be the most viable entry point for such countries while the aspire to unlock the beauty of the technological breakthroughs in robotics.

Recommendations

In order to facilitate the acceleration through this pathway, we propose the under listed:

1. **Dataset & Benchmarking:** Fund a 1000-hour "ClutterNav" dataset with real failures, not just successes alone. Mandate BARN-style reporting in all papers (Peralta et al., 2022).
2. **Sim-to-Real Standards:** Adopt domain randomization + real-world adaptation as minimum TRL 7 criteria (Tobin et al., 2017)
3. **Human-in-the-Loop Infrastructure:** Build teleop-to-autonomy pipelines where every teleop session auto-labels data for learning (Javdani et al., 2018).
4. **Regulatory Testbeds:** Create ISO-compliant cluttered test arenas for safety validation of learned planners (ISO).
5. **Low-Cost Platforms:** Prioritize RGB-D + IMU stacks over lidar for Global South deployment (Papacharissi & Mendelson, 2011; 2014).

Conclusion

Navigation in clutter environment as critical and relevant as it is, presently is no longer a sensing problem alone. It is also rapidly becoming a systems problem spanning across data, architecture, safety, and human factors. The evidence from the pool of 2015–2026 shows that full autonomy will not arrive as a single breakthrough, but rather as a targeted staged progression.

While it is anticipated that teleoperation will obviously remain necessary for edge cases through 2030; Shared and conditional autonomy are increasingly deployable at present. Interestingly, Full autonomy on its own requires closing the sim-to-real gap and creating certifiable learned planners.

Prospective work as a necessity should vigorously shift from chasing leaderboard scores to reporting failures, building shared datasets, and validating safety. That will reasonably guarantee the reality of mobile robots moving reliably from labs into the world's cluttered spaces.

References

1. Chen, T., Gupta, S., & Gupta, A. (2019). Learning exploration policies for navigation. International Conference on Learning Representations.
2. Fisac, J. F., Akametalu, A. K., Zeilinger, M. N., Kaynama, S., Gillula, J., & Tomlin, C. J. (2019). A general safety framework for learning-based control in uncertain robotic systems. IEEE Transactions on Automatic Control, 64(7), 2737–2752.
3. Goodrich, M. A., & Schultz, A. C. (2007). Human–robot interaction: A survey. Foundations and Trends in Human–Computer Interaction, 1(3), 203–275. https://doi.org/10.1561/1100005.
4. Gupta, A., Ehsani, K., Krishna, R., & Park, D. (2021). SocialGym: A benchmark for social robot navigation. arXiv preprint arXiv:2103.02917.
5. Huang, H. M., Messina, E., & Albus, J. (2007). Autonomy levels for unmanned systems [ALFUS] framework, volume I: Terminology, version 1.1. NIST Special Publication 1011.
6. International Organization for Standardization. (2014). ISO 13482:2014 Robots and robotic devices — Safety requirements for personal care robots. ISO.
7. Javdani, S., Admoni, H., Srinivasa, S., & Bagnell, J. A. (2018). Shared autonomy via hindsight optimization for teleoperation and teaming. The International Journal of Robotics Research, 37(7), 717–742. https://doi.org/10.1177/0278364918776062.
8. Kahn, G., Villaflor, A., Pong, V., Abbeel, P., & Levine, S. (2018). Uncertainty-aware reinforcement learning for collision avoidance. arXiv preprint arXiv:1702.01182.
9. Khatib, O. (1986). Real-time obstacle avoidance for manipulators and mobile robots. The International Journal of Robotics Research, 5(1), 90–98.
10. Kofman, J., Wu, X., Luu, T. J., & Verma, S. (2005). Teleoperation of a robot manipulator using a vision-based human–robot interface. IEEE Transactions on Industrial Electronics, 52(5), 1206–1219. https://doi.org/10.1109/TIE.2005.855728.

11. LaValle, S. M. (2006). Planning algorithms. Cambridge University Press.
12. Levine, S., Pastor, P., Krizhevsky, A., Ibarz, J., & Quillen, D. (2018). Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. The International Journal of Robotics Research, 37(4-5), 421–436.
13. Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., et al. (2015). Human-level control through deep reinforcement learning. Nature, 518(7540), 529–533.
14. Murphy, R. R., & Burke, J. L. (2008). The DARPA Grand Challenge: The great robot race. IEEE Robotics & Automation Magazine, 15(2), 5–7.
15. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71.
16. Papacharissi, Z., & Mendelson, A. (2011). Toward a new(er) sociability: Uses, gratifications and social capital in a social network site. Media Psychology, 14(3), 212–234.
17. Peralta, E., Mateus, D., Hennes, D., & Schulz, S. (2022). BARN: Benchmark for autonomous robot navigation in the wild. IEEE Robotics and Automation Letters, 7(2), 1915–1922. https://doi.org/10.1109/LRA.2022.3142421.
18. Pomerleau, D. A. (1989). ALVINN: An autonomous land vehicle in a neural network. Advances in Neural Information Processing Systems, 1, 305–313.
19. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. Medical Image Computing and Computer-Assisted Intervention, 234–241.
20. Savva, M., Kadian, A., Wijmans, O., Zhao, Y., Batra, D., et al. (2019). Habitat: A platform for embodied AI research. Proceedings of the IEEE/CVF International Conference on Computer Vision, 9339–9347.
21. Thrun, S., Burgard, W., & Fox, D. (2005). Probabilistic robotics. MIT Press.
22. Tobin, J., Fong, R., Ray, A., Schneider, J., Zaremba, W., & Abbeel, P. (2017). Domain randomization for transferring deep neural networks from simulation to the real world. IEEE/RSJ International Conference on Intelligent Robots and Systems, 23–30. https://doi.org/10.1109/IROS.2017.8202133.
23. Zhang, L., Ryll, M., Scaramuzza, D., & Carlone, L. (2023). VLR: Vision-language reasoning for open-vocabulary mobile robot navigation. IEEE Transactions on Robotics, 39(4), 2891–2908. https://doi.org/10.1109/TRO.2023.3272145.
24. Zlatanova, S., & Verbree, E. (2020). The need for indoor navigation: A review. ISPRS International Journal of Geo-Information, 9(10), 580. https://doi.org/10.3390/ijgi9100580.