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Indoor Autonomous Mobile Robot for Environment Mapping: a Systematic Mapping of the Literature*

Robô Móvel Autônomo Indoor para Mapeamento de Ambientes: um Mapeamento Sistemático da Literatura

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Abstract

Autonomous Mobile Robots (AMR) are increasingly used in various indoor settings, such as offices, hospitals, production lines, and industrial cargo transportation, to address specific challenges. However, the dynamic and intricate nature of these environments presents significant challenges for the development of indoor AMRs aimed at environment mapping. This article presents the results of a systematic mapping of the literature on scientific productions related to the development of indoor AMRs for environment mapping, based on research conducted in three major databases: ACM, IEEE, and Science Direct. The results reveal the main challenges in this context, particularly in terms of autonomous navigation, localization, Simultaneous Localization and Mapping (SLAM), sensor selection and integration, and map generation. In addition to these challenges, the article presents an overview of the primary algorithms and strategies for efficient SLAM and reliable mapping, as well as the main controllers, sensors, and peripherals employed in development. Lastly, strategies for energy saving in AMRs are also examined - an important but underexplored area, with few studies addressing it. By covering a broad range of techniques and technologies, this article contributes a comprehensive foundation for future research and development in the field of indoor AMRs.

Keywords: Autonomous Mobile Robots (AMR). Simultaneous Localization and Mapping (SLAM). Indoor environment.

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Resumo

Robôs Móveis Autônomos (AMR, do inglês *Autonomous Mobile Robots*) são cada vez mais utilizados em diversos ambientes indoor, como escritórios, hospitais, linhas de produção e transporte de carga industrial, para enfrentar desafios específicos. No entanto, a natureza dinâmica e complexa desses ambientes apresenta desafios significativos para o desenvolvimento de AMRs voltados ao mapeamento de ambientes. Diante desse contexto, este artigo apresenta os resultados de um mapeamento sistemático da literatura sobre produções científicas relacionadas ao desenvolvimento de AMRs indoor para mapeamento de ambientes, com base em pesquisas realizadas em três grandes bases de dados: ACM, IEEE e Science Direct. Os resultados revelam os principais desafios encontrados nesse contexto, especialmente no que diz respeito à navegação autônoma, localização, Localização e Mapeamento Simultâneos (SLAM, do inglês *Simultaneous Localization and Mapping*), seleção e integração de sensores e geração de mapas. Além desses desafios, o artigo apresenta uma visão geral dos principais algoritmos e estratégias para SLAM eficiente e mapeamento confiável, bem como dos principais controladores, sensores e periféricos utilizados no desenvolvimento. Por fim, também foram analisadas estratégias voltadas à economia de energia em AMRs, uma área importante, porém pouco explorada, com poucos estudos abordando esse tema. Ao abordar um amplo conjunto de técnicas e tecnologias, este artigo oferece uma base abrangente para futuras pesquisas e desenvolvimentos na área de AMRs indoor.

Palavras-chave: Robôs Móveis Autônomos (AMR). Localização e Mapeamento Simultâneos (SLAM). Ambiente indoor.

1 INTRODUCTION

Autonomous Mobile Robots (AMRs) are increasingly employed in indoor environments such as offices, hospitals, production lines, and facilities for industrial cargo handling. These robots offer a viable alternative for tackling various operational challenges across these domains, primarily due to their capability for continuous operation, which enhances the overall system efficiency (Mota *et al.*, 2018; Júnior *et al.*, 2021). According to Júnior *et al.* (2021), the global robotics market is expected to exceed $50 billion annually.

The autonomous navigation of AMRs relies on addressing complex tasks such as mapping, planning, obstacle avoidance, orientation, and localization, functions that are predominantly handled through Simultaneous Localization and Mapping (SLAM) techniques (Alatise; Hancke, 2020).

Despite extensive research in SLAM, indoor environments still present significant obstacles due to their dynamic nature, structural complexity, and the use of imprecise sensors (Júnior *et al.*, 2021). For instance, the presence of moving objects can cause SLAM systems to diverge if such objects are incorrectly integrated into the generated map (Inofuente-colque *et al.*, 2021). As observed by Zhang et al. (Yasuda; Martins; Cappabianco, 2020), there is still no fully successful vision-only autonomous navigation system for dynamic indoor settings.

Given the technical challenges and the increasing demand for indoor automation, it is essential to study and synthesize findings from existing literature to support and guide the development of future AMR systems in these environments.

In this context, systematic mapping is adopted as a suitable methodology to identify, organize, and analyze all relevant studies addressing a defined research question. This approach provides a high-level overview of the research landscape, revealing trends, evidence availability, and research gaps in the field (Soares; Nobre; Freitas, 2019).

This study conducts a systematic mapping of the literature specifically focused on the development of indoor AMRs for environment mapping. The selected studies were retrieved from the Association for Computing Machinery (ACM), Institute of Electrical and Electronics Engineers (IEEE), and Science Direct databases. These repositories were chosen for their high relevance in computing and engineering fields, as well as for their broad coverage of impactful publications on robotics.

The mapping aims to address the following questions: (i) What are the primary challenges in developing indoor AMRs? (ii) What algorithms and strategies are used for autonomous navigation, localization, and reliable environment mapping? (iii) What hardware components - such as microcontrollers, minicomputers, sensors, actuators, and peripherals - are employed? and (iv) What strategies are adopted to enhance energy efficiency in AMRs?

The remainder of this paper is organized as follows: Section 2 presents related works. Section 3 details the systematic mapping methodology, including the research questions and article selection process. Section 4 presents the findings and discussions. Finally, Section 5 concludes the study and proposes future research directions.

2 RELATED WORK

According to Yasuda, Martins e Cappabianco (2020), despite the existence of several autonomous navigation systems, no solution based exclusively on vision has yet proven fully successful in dynamic indoor environments. Yasuda, Martins e Cappabianco (2020) presented a systematic mapping of techniques and methods for autonomous navigation of mobile robots in indoor settings, covering localization, mapping, trajectory planning, and locomotion. However, their analysis focuses primarily on vision-based methods and includes 121 papers published between 2000 and 2017. The results indicate deficiencies in method validation, vague requirement specifications, and the absence of complete autonomous navigation systems.

Unlike that study, which was limited to vision-based methods and constrained to an earlier time window, our research adopts a broader approach to investigate diverse technological aspects of indoor AMRs, including hardware architecture, navigation algorithms, and energy strategies.

Niloy *et al.* (2021) offers practical guidance for assembling AMRs, addressing critical aspects such as locomotion, perception, localization, mapping, motion tracking, and dynamic navigation. These elements are analyzed through mathematical modeling, control strategies, and implementation challenges, while also exploring prominent algorithms and future directions for AMR development.

Fragapane *et al.* (2021) focuses on the planning and control of AMRs in intralogistics environments, including manufacturing, storage, and healthcare facilities. The authors propose a structured framework to support managerial decision-making in the deployment of AMRs.

In a separate study, Panigrahi e Bisoy (2022) emphasizes localization as a core requirement for AMR deployment. Their systematic mapping addresses key localization principles, challenges, and strategies, including RFID-based positioning and error analysis, with suggestions for future research directions.

In the context of Industry 5.0, where collaboration between humans and machines is emphasized, Farooq, Eizad e Bae (2023) reviews various energy solutions applied to commercially available terrestrial AMRs. The paper compares techniques and provides insights into selecting appropriate energy sources based on operational requirements.

Although several works explore individual aspects such as navigation, localization, and energy efficiency, no recent study has conducted a comprehensive systematic mapping focused on the overall development of indoor AMRs for environment mapping. This research aims to fill that gap by analyzing a broad set of contributions spanning algorithms, hardware platforms, and resource-efficient strategies.

3 METHOD

This study adopts the systematic mapping of the literature method as a structured approach to identify, categorize, and analyze existing research related to a defined topic. This methodology enables a comprehensive overview of the research landscape, helping to assess the presence and volume of scientific evidence in a particular domain (Soares; Nobre; Freitas, 2019). The process involves the formulation of a research protocol, which includes the definition of research questions, the construction of search strategies, and the application of inclusion and exclusion criteria for article selection.

3.1 Research Questions

The central research question guiding this study is: *What is the current landscape of scientific publications concerning the development of indoor Autonomous Mobile Robots (AMRs) for environment mapping?*

To support this objective, five specific research questions (RQs) were defined:

RQ1 What are the challenges encountered in the development of AMRs?

RQ2 What are the algorithms and strategies used for the autonomous navigation and localization of AMRs?

RQ3 What are the algorithms and strategies used in AMRs for reliable environment mapping?

RQ4 What are the main microcontrollers, minicomputers, sensors, actuators, movement mechanisms, and peripherals used in the development of AMRs for environment mapping?

RQ5 What strategies have been adopted to improve energy efficiency in AMRs?

These questions were defined to capture the key technological aspects involved in the development of indoor AMRs, including the core challenges, algorithmic and architectural solutions, and resource-efficiency strategies. The scope is intentionally broad to reflect the multidisciplinary nature of AMR systems, encompassing perception, control, computation, and power management.

The answers to these questions also allow for a secondary analysis of publication trends, institutional contributions, and geographic distribution of research on this topic, offering insight into the evolution and maturity of the field over the past decade.

3.2 Selection of Articles

The selection of articles was based on searches conducted in three databases widely recognized for their relevance in computing and engineering: the Association for Computing Machinery (ACM), the Institute of Electrical and Electronics Engineers (IEEE), and Science

Direct. These repositories were chosen because they concentrate high-impact publications in the areas of robotics, artificial intelligence, and embedded systems, ensuring both coverage and quality of the sources.

The searches were conducted in October 2022 using a unified search string structured to identify studies on AMRs applied to environment mapping. The query targeted titles and abstracts and was written in English to maximize relevance across international publications:

S1 (Autonomous Mobile Robots OR AMR) AND (mapping OR map generation) AND ((challenges OR difficulties) OR (algorithm OR artificial intelligence OR machine learning OR internet of things OR IOT) OR (microcontroller OR minicomputer OR mini computer OR sensor OR actuator OR peripheral OR designs OR configuration OR settings) OR (energy saving OR energy-saving OR battery saving OR energy efficiency)))

The search string was designed to align with the multidimensional scope of this study, which includes technical, algorithmic, and architectural elements of AMR development in indoor settings.

Additionally, the search was limited to articles published from 2012 to October 2022. This decision reflects the rapid technological advancement in robotics and related fields, and a 10-year window was considered appropriate to capture the most relevant and updated developments.

An initial set of 129 articles was retrieved. Duplicate entries were then removed, and abstracts were reviewed to apply the following exclusion criteria:

- Review papers.
- Papers in languages other than English.
- Papers focused on non-terrestrial AMRs.
- Papers focused on large-scale AMRs.
- Papers focused on outdoor AMRs.
- Papers focused on articulated AMRs.
- Duplicated papers (only the most updated version was retained).
- Publications not accessible in full text.

After applying all criteria, 79 articles remained. Table 1 summarizes the number of articles retrieved before applying the exclusion criteria (Initial Count column) and after applying the criteria (Final Selection column).

Table 1 – Number of articles retrieved and selected by database

Database	Initial Count	Final Selection
ACM	17	14
IEEE	79	57
Science Direct	33	8
Total	129	79

Source: Authors.

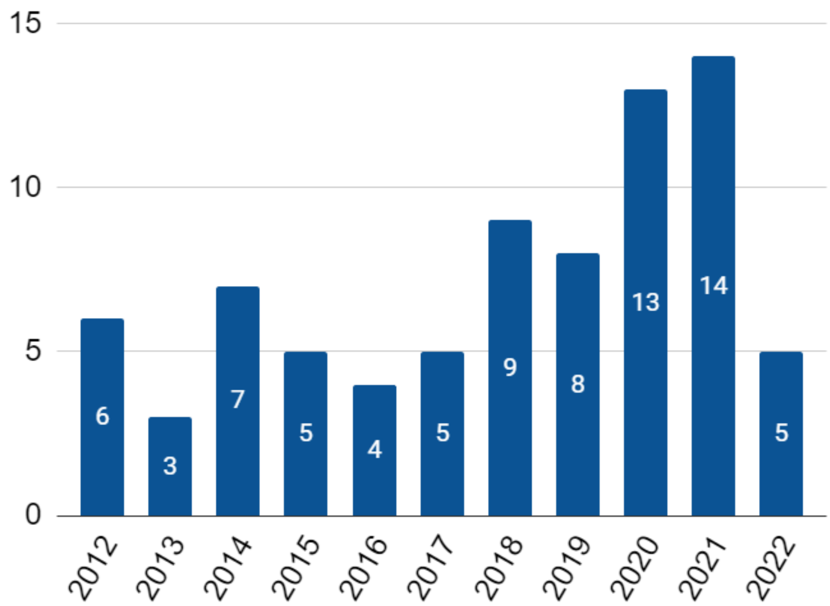
This final selection represents a refined dataset of studies strictly aligned with the defined scope and research questions, ensuring the relevance and depth required for a meaningful systematic mapping.

4 RESULTS AND DISCUSSION

Figure 1 presents the temporal distribution of the selected articles, illustrating the number of publications per year. The data indicate a steady increase in research activity on Autonomous Mobile Robots (AMRs), with a significant rise observed after 2019. This trend reflects both the rapid technological evolution in artificial intelligence and robotics, and the growing demand for autonomous systems across sectors such as logistics, healthcare, and manufacturing (Júnior *et al.*, 2021).

In addition, the COVID-19 pandemic emphasized the value of automation in reducing human exposure and maintaining operational continuity, which likely contributed to the recent surge in related studies.

Figure 1 – Temporal distribution of articles



Source: Authors.

It is also important to note that the apparent decline in the number of articles in 2022 may be attributed to the data collection period, which was conducted in October 2022. Due to the typical delay between conducting research and publishing results, it is likely that additional publications from late 2022 were not yet indexed at the time of this study. Therefore, the final count of articles for that year may be higher than reflected here.

As for the geographical distribution of research, China was the most represented country, accounting for 18 articles, or 22.78% of the total. It was followed by the United States (10 articles), Japan (6), South Korea (6), Indonesia (4), and India (4). Several other countries contributed with three or fewer articles. Frame 1 lists the countries and the corresponding number of papers, along with the respective references.

Frame 1 – Number and researches by countries where the universities that conducted them are located

Country	Total	Papers
China	18	(Gao; Li, 2020) (Chai *et al.*, 2018) (Wang *et al.*, 2016) (Zhang; Jiang; Wang, 2016) (Yan *et al.*, 2018) (Chen *et al.*, 2021) (Zheng; He; Pan, 2022) (Shi *et al.*, 2019) (Pan *et al.*, 2019) (Yuan *et al.*, 2022) (Yang *et al.*, 2020) (Zeng; Si, 2019) (Yasuda; Ohkura; Yamada, 2013) (Zhi; Xuesong, 2018) (Liu *et al.*, 2021) (Zhang *et al.*, 2020) (Yuan *et al.*, 2021) (Zhang *et al.*, 2021)
United States	10	(Li *et al.*, 2019) (Matta; Chalhoub, 2013) (Walcott-bryant *et al.*, 2012) (Smith *et al.*, 2013) (Argush *et al.*, 2020) (Bae; Lee, 2018) (Janah; Fujimoto, 2018a) (Deshpande *et al.*, 2014) (Nashed *et al.*, 2021) (Martin *et al.*, 2020)
Japan	6	(Deguchi *et al.*, 2014) (Noaman; Al-shibaany; Al-wais, 2020) (Fukui *et al.*, 2022) (Du; Ai; Feng, 2020) (Janah; Fujimoto, 2018b) (Ohnishi; Imiya, 2013)
South Korea	6	(Jo *et al.*, 2014) (Lee; Chung, 2021) (Laskar; Tawhid; Chung, 2012) (Dinh; Kim, 2020) (Lee; Chang, 2016) (Talwar; Jung, 2019)
Indonesia	4	(Attamimi *et al.*, 2022) (Arthaya; Pratama; Wu, 2014) (Anggraeni *et al.*, 2021) (Budiman; Laurensia; Arthaya, 2021)
India	4	(Li *et al.*, 2019) (Jain; Kumar; Nagla, 2015) (Maria *et al.*, 2021) (Singha; Ray; Samaddar, 2017)
Italy	3	(Li, 2015) (Luperto *et al.*, 2019) (Riva; Amigoni, 2017)
Portugal	3	(Faria; Moreira, 2021) (Júnior *et al.*, 2021) (Dogru; Marques, 2015)
Germany	3	(Schwendner, 2012) (Jacobson; Chen; Milford, 2015) (MÜller *et al.*, 2022)
Brazil	3	(Oliveira; Carvalho; BrandÃo, 2018) (Mota *et al.*, 2018) (Fernandes; Oliveira; Neto, 2022)
Spain	2	(Jaenal; Moreno; Gonzalez-jimenez, 2019) (Prieto *et al.*, 2017)
Canada	2	(Wang; Jenkin; Dymond, 2014) (Clement *et al.*, 2020)
Hungry	2	(Hajdu *et al.*, 2020) (Kis; Csempesz; Csáji, 2021)
Turkey	2	(KÖseoğlu; Çelik; Pektas, 2017) (Uslu *et al.*, 2015)
United Kingdom	2	(Tomy *et al.*, 2020) (Rigatos, 2012)
Peru	1	(Inofuente-colque *et al.*, 2021)
France	1	(Gokhool *et al.*, 2014)
Bulgaria	1	(Hamadi *et al.*, 2020)
Finland	1	(Qingqing *et al.*, 2019)
Mexico	1	(Roa-borbolla *et al.*, 2017)
Australia	1	(Cadena; KoŠeckÁ, 2014)
Malaysia	1	(Baharom *et al.*, 2020)
Croatia	1	(Mutlu; Uyar, 2012)
Russia	1	(Baltashov; Semakova, 2018)

Source: Authors.

Regarding the publication venues of the selected articles, Frame 2 presents the main journals and conferences in which the studies were published. Other venues not listed in the table had only one publication each related to the scope of this research.

Frame 2 – Venues with higher number papers

Venue	Total	Papers
International Conference on Intelligent Robots and Systems	5	(Walcott-bryant *et al.*, 2012) (Jacobson; Chen; Milford, 2015) (Deshpande *et al.*, 2014) (Nashed *et al.*, 2021) (Martin *et al.*, 2020)
IEEE ACCESS	4	(Shi *et al.*, 2019) (Mota *et al.*, 2018) (Yuan *et al.*, 2022) (Yang *et al.*, 2020)
IFAC Symposium on Robot Control	2	(Mutlu; Uyar, 2012) (Baltashov; Semakova, 2018)
European Conference on Mobile Robots	2	(Dogru; Marques, 2015) (Tomy *et al.*, 2020)
International Conference on Mechatronics, Robotics and Systems Engineering	2	(Anggraeni *et al.*, 2021) (Budiman; Laurensia; Arthaya, 2021)
Annual Conference of the IEEE Industrial Electronics Society	2	(Faria; Moreira, 2021) (Janah; Fujimoto, 2018a)
IEEE International Conference on Real-time Computing and Robotics	2	(Wang *et al.*, 2016) (Du; Ai; Feng, 2020)
IEEE International Conference on Mechatronics and Automation	2	(Zhang; Jiang; Wang, 2016) (Liu *et al.*, 2021)
IEEE International Conference on Robotics and Automation	2	(Lee; Chung, 2021) (Cadena; KoŠeckÁ, 2014)

Source: Authors.

4.1 RQ1 – What are the challenges encountered in the development of AMR?

Several studies on Autonomous Mobile Robots (AMRs) highlight various challenges faced during their development. Frame 3 categorizes the primary challenges into five main types - navigation, SLAM, localization, sensors, and map generation - listing the articles that identify each type as either the main challenge or a secondary one.

Frame 3 – Challenges Encountered in the Development of AMR

Type of challenge	Papers (main challenge)	Papers (challenge, but not as the main one)
Navigation	(Li *et al.*, 2019) (Oliveira; Carvalho; BrandÃo, 2018) (Li, 2015) (Qingqing *et al.*, 2019) (Chai *et al.*, 2018) (Luperto *et al.*, 2019) (Riva; Amigoni, 2017) (Hamadi *et al.*, 2020) (Hajdu *et al.*, 2020) (Laskar; Tawhid; Chung, 2012) (Pan *et al.*, 2019) (Schwendner, 2012) (Budiman; Laurensia; Arthaya, 2021) (Singha; Ray; Samaddar, 2017) (Kis; Csempesz; Csáji, 2021) (Ohnishi; Imiya, 2013)	(Li *et al.*, 2019) (Chai *et al.*, 2018) (Ohnishi; Imiya, 2013)
SLAM	(Attamimi *et al.*, 2022) (Gao; Li, 2020) (Wang; Jenkin; Dymond, 2014) (Jo *et al.*, 2014) (Zhang; Jiang; Wang, 2016) (Zheng; He; Pan, 2022) (Fukui *et al.*, 2022) (Zhi; Xuesong, 2018) (Zhang *et al.*, 2020) (Zhang *et al.*, 2021) (Liu *et al.*, 2021) (Jacobson; Chen; Milford, 2015) (Talwar; Jung, 2019) (Janah; Fujimoto, 2018a) (Du; Ai; Feng, 2020) (Janah; Fujimoto, 2018b)	(Schwendner, 2012) (Yan *et al.*, 2018) (Liu *et al.*, 2021) (Zhang *et al.*, 2020) (Kis; Csempesz; Csáji, 2021)
Localization	(Noaman; Al-shibaany; Al-wais, 2020) (Maria *et al.*, 2021) (Clement *et al.*, 2020) (Mota *et al.*, 2018) (Baharom *et al.*, 2020) (Ohnishi; Imiya, 2013)	(Mota *et al.*, 2018)
Sensor	(Deguchi *et al.*, 2014) (Jaenal; Moreno; Gonzalez-jimenez, 2019) (Yuan *et al.*, 2022) (Yang *et al.*, 2020) (Cadena; KoŠeckÁ, 2014)	(Yuan *et al.*, 2021) (Ohnishi; Imiya, 2013) (Ohnishi; Imiya, 2013)
Map Generation	(Yan *et al.*, 2018) (Zeng; Si, 2019) (Nashed *et al.*, 2021) (Martin *et al.*, 2020)	(KÖseoğlu; Çelik; Pektas, 2017) (Zhi; Xuesong, 2018) (Mota *et al.*, 2018) (Zhang *et al.*, 2020) (Ohnishi; Imiya, 2013)

Source: Authors.

Navigation emerged as the most cited challenge across the selected studies. Articles in this category discussed difficulties such as: the development and assessment of optimized navigation strategies in unknown environments (Li *et al.*, 2019; Li, 2015; Qingqing *et al.*, 2019; Luperto *et al.*, 2019; Chai *et al.*, 2018); complete and efficient area coverage (Riva; Amigoni, 2017); path optimization (Laskar; Tawhid; Chung, 2012); information abstraction for target location (Singha; Ray; Samaddar, 2017); and adaptation to dynamic environments (Ohnishi; Imiya, 2013).

SLAM (Simultaneous Localization and Mapping) was the second most prevalent challenge. Issues reported include: localization accuracy (Attamimi *et al.*, 2022; Schwendner, 2012; Talwar; Jung, 2019; Janah; Fujimoto, 2018a; Du; Ai; Feng, 2020); odometry precision (Zhi; Xuesong, 2018; Lee; Chang, 2016; Zhang *et al.*, 2020); and the robustness of relocalization processes to support autonomous navigation (Zhang *et al.*, 2020).

Regarding localization, the main problems identified were accuracy (Noaman; Al-shibaany; Al-wais, 2020), high cost (Baharom *et al.*, 2020), and long-term consistency in metric self-localization (Clement *et al.*, 2020).

Sensor-related challenges include: human-focused environmental monitoring (Deguchi *et al.*, 2014), dynamic object recognition (Yang *et al.*, 2020), environmental sensing (Yuan *et al.*, 2022), and managing data overlap from multiple sensors (Cadena; KoŠeckÁ, 2014; Yuan *et al.*, 2021).

In map generation, challenges involve: estimating robot position while building the environment map (Mota *et al.*, 2018; Yan *et al.*, 2018; Zeng; Si, 2019); achieving high-precision and consistent maps (Zhang *et al.*, 2020); and enabling real-time spatial reasoning from sensory data (Ohnishi; Imiya, 2013).

Other isolated but noteworthy challenges include: converting spatial points into images (Bae; Lee, 2018); human behavior prediction (Zheng; He; Pan, 2022); operation in multi-robot systems (Yasuda; Ohkura; Yamada, 2013); system architecture efficiency (Fernandes; Oliveira; Neto, 2022); AMR-to-computer communication (Anggraeni *et al.*, 2021); ethical decision-making (Smith *et al.*, 2013); and high-precision time synchronization (Yuan *et al.*, 2021).

Understanding these challenges provides a foundation for future research in the development of indoor AMRs. By identifying these obstacles early, researchers can design more resilient systems that proactively address known limitations.

4.2 RQ2 – What are the algorithms and strategies used for autonomous navigation and localization of AMR?

Autonomous navigation and localization emerged as the most frequently cited challenges in the reviewed articles, with navigation, SLAM, and localization jointly accounting for over 82% of the references to primary challenges in AMR development.

Consequently, the reviewed studies proposed various strategies to address these problems. One of the most widely adopted families of algorithms is SLAM (Simultaneous Localization and Mapping) (Qingqing *et al.*, 2019; Gao; Li, 2020; Hamadi *et al.*, 2020; Hajdu *et al.*, 2020; Pan *et al.*, 2019; Júnior *et al.*, 2021; Fukui *et al.*, 2022; Schwendner, 2012; Roa-borbolla *et al.*, 2017; Martin *et al.*, 2020; MÜller *et al.*, 2022). Prominent variants include 3D Fast-SLAM (Jo *et al.*, 2014), Fast-SLAM (Wang *et al.*, 2016), Hector SLAM (Maria *et al.*, 2021), Visual SLAM (Shi *et al.*, 2019), ORB-SLAM-2 (Anggraeni *et al.*, 2021; Yang *et al.*, 2020), MGC-VSLAM (Yang *et al.*, 2020), and RD-SLAM (Nashed *et al.*, 2021). SLAM is essential for enabling AMRs to construct and update a map while simultaneously determining their own position, a capability vital for autonomous navigation, obstacle avoidance, and task execution (Attamimi *et al.*, 2022; Jo *et al.*, 2014).

The Robot Operating System (ROS) was another frequently referenced tool (Hajdu *et al.*, 2020; Maria *et al.*, 2021; Argush *et al.*, 2020; Faria; Moreira, 2021; Anggraeni *et al.*, 2021; Zhi; Xuesong, 2018; Talwar; Jung, 2019; Baltashov; Semakova, 2018). ROS offers a modular and flexible framework that streamlines the integration of diverse hardware and software components. Its vast library and global community accelerate development and foster the adoption of advanced algorithms in real-world robotic systems (Zhi; Xuesong, 2018).

Filtering techniques are commonly used to fuse sensor data, correct measurement errors, and manage uncertainty in navigation (Li *et al.*, 2019). Notable approaches include: the Extended Kalman Filter (EKF) (Attamimi *et al.*, 2022; Gao; Li, 2020; Laskar; Tawhid; Chung, 2012), Sensor Fusion (Li *et al.*, 2019), the Madgwick Filter (Attamimi *et al.*, 2022), Rao-Blackwellized Particle Filtering (Jo *et al.*, 2014), Multi-Sensor Fusion System (MSFS) (Dinh; Kim, 2020), and GC Filter (Yang *et al.*, 2020).

Odometry was also highlighted as a crucial method, particularly in indoor settings where GPS may be unavailable or unreliable. To improve positional accuracy, techniques such as Visual-Inertial Odometry (VIO) (Qingqing *et al.*, 2019; Zhang *et al.*, 2020; Zhang *et al.*, 2021), Visual Odometry (Gokhool *et al.*, 2014), and the use of Odometry Sensors (Baharom *et al.*, 2020) were adopted.

Machine learning (ML) algorithms are increasingly used to enhance AMR decision-making in dynamic environments. Cited methods include Artificial Neural Networks (ANN) or Deep Neural Networks (DNN) (Gao; Li, 2020; Clement *et al.*, 2020; Hajdu *et al.*, 2020; Yuan *et al.*, 2022), Deep Reinforcement Learning (DRL) (Zheng; He; Pan, 2022; Yasuda; Ohkura; Yamada, 2013), probabilistic localization using Adaptive Monte Carlo Localization (AMCL) (Maria *et al.*, 2021; Júnior *et al.*, 2021), Bayes Rule Learning (Yasuda; Ohkura; Yamada, 2013; Bae; Lee, 2018), hierarchical exploration planners with reinforcement learning (Zheng; He; Pan, 2022), K-means clustering (Laskar; Tawhid; Chung, 2012), Behavior-Based Learning (MÜller *et al.*, 2022), and the Deep Q-Network (DQN) framework (Li *et al.*, 2019).

Additional strategies reported include the use of artificial color beacons for localization (Noaman; Al-shibaany; Al-wais, 2020), search algorithms (Oliveira; Carvalho; BrandÃo, 2018), decentralized multi-robot collision avoidance via Proximal Policy Optimization (Zheng; He; Pan, 2022), RFID and Petri Net integration (Mota *et al.*, 2018), graph-based models (Budiman; Laurensia; Arthaya, 2021), Monte Carlo methods integrated with laser sensors via ROS (Talwar; Jung, 2019), Swarm Intelligence techniques like Particle and Firefly algorithms (Janah; Fujimoto, 2018a), and the application of Markov Random Fields and Conditional Random Fields (Cadena; KoŠeckÁ, 2014).

4.3 RQ3 – What are the algorithms and strategies used in AMRs for reliable environment mapping?

In the development of AMRs, reliable mapping emerges as a critical challenge. Key issues include constructing consistent maps and determining the robot's position within them (Mota *et al.*, 2018; Yan *et al.*, 2018; Zeng; Si, 2019), distinguishing between static and dynamic elements in the environment (Ohnishi; Imiya, 2013), and achieving high resolution and precision in the generated maps (Zhang *et al.*, 2020).

Reliable environment mapping is essential to enable safe and efficient autonomous navigation. It provides a structured spatial representation that allows AMRs to interpret surroundings, identify landmarks and obstacles, and determine safe, optimized paths. This facilitates real-time decision-making, minimizes collisions, and enhances task execution.

Frame 4 presents the main algorithms cited for reliable map generation. G-mapping is among the most widely adopted, known for its ability to simultaneously construct maps and localize the robot using sensor data. Other relevant algorithms include Real-Time Appearance-Based Mapping (RTAB-Map), which utilizes RGB-D sensor data; Greedy Randomized Adaptive Search Procedure (GRASP), for procedural mapping; voxel-based methods for 3D representation; and Cartographer, for robust 2D and 3D mapping and localization.

Frame 4 – Main algorithms used for generating reliable maps

Algorithm	Description	Papers
G-mapping	Accurate map construction	(Hajdu *et al.*, 2020) (Uslu *et al.*, 2015) (Baharom *et al.*, 2020) (Wang *et al.*, 2016)
RTAB-Map	Processing RGB-D data and generating real-time maps	(Attamimi *et al.*, 2022) (Argush *et al.*, 2020)
GRASP	Procedural map generation	(Riva; Amigoni, 2017)
Voxel map	Three-dimensional representation of the environment	(Jo *et al.*, 2014)
Cartographer	Map construction and AMR position determination	(Du; Ai; Feng, 2020)

Source: Authors.

Beyond algorithmic solutions, some articles proposed techniques addressing dynamic and complex indoor environments. For instance, (Inofuente-colque *et al.*, 2021) presented a 2D mapping approach for dynamic environments with frequently moving objects. Meanwhile, (Jain; Kumar; Nagla, 2015) introduced a corner-detection-enhanced method that improved mapping accuracy and reduced navigational complexity.

4.4 RQ4 – What are the main microcontrollers, minicomputers, sensors, actuators, movement mechanisms, and peripherals used in the development of AMRs for environment mapping?

The choice of controller is fundamental in AMR development, as it directly influences system performance and efficiency in relation to its intended application. Frame 5 summarizes the primary controllers used and the corresponding references.

Frame 5 – Main controllers used for the development of AMR

Controller	**Papers**
Arduino Microcontroller	(Attamimi *et al.*, 2022; Deguchi *et al.*, 2014; Mota *et al.*, 2018)
Jetson Minicomputer	(Attamimi *et al.*, 2022; Argush *et al.*, 2020; Faria; Moreira, 2021)
Computer	(Deguchi *et al.*, 2014; Yang *et al.*, 2020; Zeng; Si, 2019; Baltashov; Semakova, 2018)

Source: Authors.

Microcontrollers, such as Arduino Uno, Nano, and Mega, were primarily used in simpler systems (Attamimi *et al.*, 2022; Deguchi *et al.*, 2014; Mota *et al.*, 2018). For more complex tasks requiring greater processing power, minicomputers like Jetson were frequently adopted (Attamimi *et al.*, 2022; Argush *et al.*, 2020; Faria; Moreira, 2021). Traditional computers were preferred in implementations demanding advanced computational resources and algorithm complexity (Deguchi *et al.*, 2014; Yang *et al.*, 2020; Zeng; Si, 2019; Baltashov; Semakova, 2018). In some works, the use of GPUs was also reported to accelerate processing (Hajdu *et al.*, 2020; Pan *et al.*, 2019).

Frame 6 presents the main sensors utilized in AMRs, which play a critical role in perception and interaction with the environment.

Frame 6 – Main sensors used for the development of AMR

Sensor	Papers
Camera	(Attamimi *et al.*, 2022; Deguchi *et al.*, 2014; Jo *et al.*, 2014; Faria; Moreira, 2021; Bae; Lee, 2018; Wang; Jenkin; Dymond, 2014; Noaman; Al-shibaany; Al-wais, 2020; Hamadi *et al.*, 2020; Hajdu *et al.*, 2020; Argush *et al.*, 2020; Shi *et al.*, 2019; Uslu *et al.*, 2015; Anggraeni *et al.*, 2021; Yuan *et al.*, 2022; Yasuda; Ohkura; Yamada, 2013; Dinh; Kim, 2020; Talwar; Jung, 2019; Yang *et al.*, 2020; Yuan *et al.*, 2021; Baltashov; Semakova, 2018)
LiDAR	(Hajdu *et al.*, 2020; Maria *et al.*, 2021; Argush *et al.*, 2020; Pan *et al.*, 2019; Faria; Moreira, 2021; Dinh; Kim, 2020; Roa-borbolla *et al.*, 2017; Baharom *et al.*, 2020; Yuan *et al.*, 2021; Kis; Csempesz; Csáji, 2021; Baltashov; Semakova, 2018; Luperto *et al.*, 2019; Gao; Li, 2020; Chai *et al.*, 2018; Prieto *et al.*, 2017; Talwar; Jung, 2019)
Distance sensors	(Hamadi *et al.*, 2020; Maria *et al.*, 2021; Budiman; Laurensia; Arthaya, 2021; Yuan *et al.*, 2022; Yasuda; Ohkura; Yamada, 2013)
Gyroscope	(Attamimi *et al.*, 2022; Gao; Li, 2020)
GPS	(Hamadi *et al.*, 2020; Smith *et al.*, 2013)
Sonar sensors	(Wang; Jenkin; Dymond, 2014)
LSM303D Compass	(Noaman; Al-shibaany; Al-wais, 2020)
RFID	(Mota *et al.*, 2018)
Speed sensor	(Yuan *et al.*, 2022)
Wheel encoders	(Baharom *et al.*, 2020)

Source: Authors.

Among the sensors, cameras - especially Microsoft Kinect - were heavily utilized for visual SLAM and object recognition (Deguchi *et al.*, 2014; Jo *et al.*, 2014; Faria; Moreira, 2021; Bae; Lee, 2018; Baltashov; Semakova, 2018). LiDAR sensors were also commonly applied for precise spatial mapping; examples include Ouster OS-11 (3D), RP LiDAR A2 (2D), and Hesai Pandar40M (Hajdu *et al.*, 2020; Maria *et al.*, 2021; Argush *et al.*, 2020; Yuan *et al.*, 2021; Kis; Csempesz; Csáji, 2021). Ultrasonic distance sensors were frequently used for simpler proximity detection tasks (Maria *et al.*, 2021; Budiman; Laurensia; Arthaya, 2021; Yuan *et al.*, 2022).

Despite its usefulness in outdoor navigation, GPS is often ineffective indoors due to signal attenuation through physical barriers, resulting in limited precision.

Frame 7 lists the main chassis models employed, which are essential for defining mobility, mechanical support, and task-specific design constraints.

Frame 7 – Main chassis used for AMR development

Chassis	**Papers**
TurtleBot2	(Deguchi *et al.*, 2014; Zheng; He; Pan, 2022)
Robocom	(Luperto *et al.*, 2019)
Modified Nomad SuperScout	(Wang; Jenkin; Dymond, 2014)
AION ROBOTICS R1 UGV	(Argush *et al.*, 2020)
Festo Robotino 3 mobile robot	(Anggraeni *et al.*, 2021)
Acrylic chassis	(Mota *et al.*, 2018)
Pioneer-3DX Robot	(Bae; Lee, 2018)

Source: Authors.

4.5 RQ5 – What strategies have been adopted to improve energy efficiency in AMRs?

Energy efficiency is a critical factor in the development of Autonomous Mobile Robots (AMRs), directly impacting their autonomy and operational viability. However, energy-saving strategies were addressed in only a small portion of the reviewed literature, with just 6.3% of the selected articles discussing this topic explicitly (Gao; Li, 2020; Wang; Jenkin; Dymond, 2014; Faria; Moreira, 2021; Du; Ai; Feng, 2020; Tomy *et al.*, 2020).

One of the most frequently cited strategies involves path planning algorithms, which help AMRs avoid unnecessary travel by optimizing routes. This minimizes energy consumption, particularly since locomotion is one of the most power-intensive operations in mobile robots (Gao; Li, 2020). Additionally, (Wang; Jenkin; Dymond, 2014) note that reduced movement in corridors with limited visibility further contributes to energy conservation.

Efficient navigation strategies also contribute to energy savings by reducing redundant movements and avoiding collisions (Gao; Li, 2020). These strategies often rely on sensors for obstacle detection, enabling robots to make real-time decisions that reduce wasteful actions.

Another effective strategy is optimizing sensor usage. As discussed by (Faria; Moreira, 2021), sensors can be energy-intensive, especially when used continuously. Adaptive sampling algorithms and selective deactivation of sensors when they are not needed help reduce power consumption.

Control algorithms are equally important, as they enable AMRs to adjust speed and direction based on environmental factors. For instance, reducing speed in narrow corridors or low-visibility areas can lead to significant energy savings (Du; Ai; Feng, 2020).

Hardware selection also plays a pivotal role. The use of low-power microcontrollers and minicomputers, such as the STM32, can significantly enhance energy efficiency by reducing baseline consumption during operation (Du; Ai; Feng, 2020).

Finally, (Tomy *et al.*, 2020) propose a strategy based on battery management using Markov decision processes. This approach models battery dynamics to ensure that energy reserves are used optimally, ensuring that the AMR has sufficient charge for essential tasks.

5 CONCLUSION

This study presented a systematic mapping of the literature on the development of indoor Autonomous Mobile Robots (AMRs) for environment mapping, based on articles retrieved from the ACM, IEEE, and Science Direct databases.

The analysis revealed that the most frequently cited challenges in AMR development are related to navigation, SLAM, and localization. These challenges primarily involve the creation of effective and optimized navigation strategies in unknown environments, achieving high precision in simultaneous localization and mapping, and ensuring odometry accuracy. Additional difficulties were also noted, such as the proper selection and utilization of sensors and the construction of reliable environmental maps.

Regarding algorithms and strategies for autonomous navigation and localization, SLAM methods were the most prevalent. These allow AMRs to construct and continuously update environmental maps while tracking their own position. The Robot Operating System (ROS) was widely adopted for software integration and modularity, while sensor fusion techniques and filters were used to improve data accuracy and robustness. Machine Learning approaches were also leveraged to improve decision-making in dynamic environments. Other methods such as odometry, beacon usage, search algorithms, and RFID were also observed.

Reliable environment mapping, identified as a major development challenge, plays a key role in autonomous navigation. Among the mapping strategies, G-mapping stood out due to its real-time, sensor-driven capabilities for accurate map construction.

In terms of hardware, Arduino and Jetson were the most frequently used microcontrollers and minicomputers, respectively. The majority of the reviewed articles utilized cameras and LiDAR sensors, while others incorporated distance sensors, gyroscopes, sonar sensors, compasses, RFID, speed sensors, wheel encoders, and GPS. Different chassis types were also identified, reflecting varying mobility and application requirements.

Despite the critical importance of energy efficiency in AMR development, only 6.3% of the analyzed articles discussed energy-saving strategies. Among those that did, the main techniques included optimized path planning, adaptive sensor usage, control algorithms for speed regulation, hardware efficiency improvements, and battery management based on Markov decision processes.

The study also provided insights into publication trends, geographical distribution of research, and dissemination venues. A significant increase in publications was observed post-2019, with China leading in research output, followed by the United States, Japan, and South

Korea. Key journals and conferences were also identified.

Overall, the main contribution of this work is the organization and analysis of relevant scientific literature, offering a consolidated view of the current state and challenges in developing indoor AMRs for mapping tasks. The findings serve as a useful foundation for future research, supporting both academic investigations and practical developments.

As future work, we propose conducting comparative analyses of the key technologies identified in this study, with the goal of developing a detailed guide to optimal AMR architectures. Such a guide would match specific contexts and objectives with suitable components, algorithms, and strategies. Additionally, further exploration of energy-saving techniques in AMR design is warranted, given the limited coverage of this topic in existing literature.

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