# Bridging the Gap: Machine Learning and Vision Neural Networks in Autonomous Vehicles for the Aging Population

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***Abstract*—As autonomous vehicles (AVs) evolve recently, it is necessary to address the unique needs of the aging population group. They can get a significant benefit from this technology. This scoping review focus the role of machine learning and vision neural networks in autonomous vehicles. A focus on enhancing safety, usability, and trust for elderly users will be mentioned as well. It systematically reviews existing literature to identify how these technologies address the cognitive and physical challenges faced by older adults. The review highlights key advancements in AV technology, such as adaptive interfaces and assistive features. That can enhance the driving experience for the elderly. Additionally, it investigates factors influencing trust and acceptance of AVs among older adults, emphasizing the importance of transparent and user-friendly design. Although, the despite notable progress has been made, the significant gaps remain in understanding how to optimize these technologies to meet the diverse needs of elderly passengers. The review identifies areas for future research, including personalized AV systems and regulatory frameworks that support designs friendly to the elderly. By addressing these gaps, the study aims to contribute to developing autonomous vehicles that are inclusive and accessible. It will make the mobility and quality of life for the aging population increased. This review underscores the importance of integrating machine learning and vision neural networks in designing AVs that cater to the unique needs of older adults. It was also offering valuable insights for researchers, policymakers, and industry stakeholders advancing autonomous vehicle technology.**

***Keywords*—*Autonomous vehicles; machine learning; vision neural network; human-computer interaction; aging population; artificial intelligence***

## I. INTRODUCTION

### A. *Overview of Autonomous Vehicles (AVs) and their Increasing Role in Transportation*

Autonomous vehicles (AVs), also known as self-driving cars. It's capable of operating with reduced or no human input. AVs are making a revolution of the transportation landscape by offering new possibilities for mobility and accessibility [1]. These vehicles utilize a combination of sensors, cameras, and algorithms to navigate roads without human intervention [2]. The progress in vehicles' technology have accelerated the development and deployment of AVs over the past decade. The industry has positioned them as a transformative force in the automotive industry [3]. The promise of enhanced safety, efficiency, and convenience has fueled interest in AVs from governments, industry stakeholders, and consumers alike [4]. AVs offer a potential solution to reduce traffic problems as urbanization and population growth place increasing demands on transportation infrastructure. For instance, improve road safety and provide accessible transportation options for diverse populations [3].

### B. *Introduction to Machine Learning and Vision Neural Networks in AVs*

Machine learning and vision neural networks are key technologies driving the evolution of autonomous vehicles [5]. Machine learning algorithms make AVs to learn from large datasets. This allowing them to recognize patterns, make decisions, and adapt to changing environments in different driving scenarios [6]. Vision neural networks is a subset of machine learning. They are particularly crucial for AVs as they process and interpret visual information from cameras and sensors. These networks enable AVs to detect and identify objects, interpret traffic signals, and navigate complex environments [7]. Technologies like Tesla's Full Self-Driving (FSD) system exemplify the application of vision neural networks in AVs, allowing for advanced features such as automated lane changes and obstacle avoidance [8]. The integration of these technologies enhances the capability of AVs in real-world conditions, so AVs can operate safely and efficiently on the road.

### C. *Importance of Addressing the Needs of the Aging Population in the Context of AV Technology*

The aging population represents a significant and growing demographic, especially in Australia. Approximately 4.2 million people were aged 65 and over on 30 June 2020, this occupied 16% of Australia's total population [9]. This group will stand to benefit greatly from autonomous vehicle technology. As the age growing, elderly may face cognitive and physical challenges that impact their ability to drive safely. Autonomous vehicles can provide a more mobility and independence ability to elderly individuals. It will reduce elder people's reliance on public transportation or family assistance [10]. However, it's essential to address the specific needs and preferences of older adults in the design and implementation of AV technology to fully meet these benefits. This includes considerations for cognitive load, ease of use, and safety features that cater to the physical limitations and cognitive changes associated with aging [11]. For example, AV technology can be developed to enhance their quality of life and promote social inclusion to focus on the unique requirements which elderly need. Additionally, understanding and addressing the trust and acceptance factors among elderly users is critical for successful AV adoption. As this group of people continues to grow, incorporating their needs into AV design will improve accessibility and AVs can contribute positively to societal well-being at the same time [12].

## II. Methodology

The methodology for this scoping review follows a structured approach to ensure comprehensive coverage of the literature related to machine learning and vision neural networks in autonomous vehicles (AVs) for the aging population. This section outlines the framework used for conducting the review, the search strategy employed to identify relevant studies, the criteria for inclusion and exclusion, and the process of data extraction and analysis.

### A. Scoping Review Framework

This scoping review is conducted following the framework proposed by Arksey and O'Malley (2005), which is widely used in scoping reviews to map the existing literature and identify gaps in research. The framework of the scoping review includes of five key stages:

1) *Identifying the research question:* The primary research question guiding this review is: "What is the current stage of research on machine learning and vision neural networks in autonomous vehicles? How are they can help the aging population?"

2) *Identifying relevant studies:* A comprehensive search of academic databases was conducted to identify relevant literature. The studies published in the last four years (2020-2024) will be focused, aims to capture the most recent advancements in this field.

3) *Selecting studies:* The study selection process should followed by predefined inclusion and exclusion criteria, to ensure only the pertinent studies in the review inclusion.

4) *Charting the data:* Data from selected studies were extracted and charted to facilitate analysis and synthesis.

5) *Collating, summarizing, and reporting the results:* The results were collated, summarized, and reported to provide an overview of the current state of research and identify gaps and future research directions.

### B. Search Strategy

The search strategy was designed to capture a comprehensive set of studies related to the use of machine learning and vision neural networks in AVs for elderly users. The following steps were taken to implement the search strategy:

1) *Databases and sources:* The literature search was conducted using the following academic databases, which are known for their extensive coverage of scientific and technical publications:

*a) PubMed:* For biomedical and life sciences literature.

*b) IEEE Xplore:* For engineering and technology-focused studies.

*c) Google Scholar:* For a broad search across various disciplines.

*d) Scopus:* For a wide range of reviewed literature in the fields of science, technology, medical, and social sciences.

2) *Keywords and search terms:* The search terms were selected by the keywords of this review topic to make sure it will catch the relevant literature on the topic. Keywords used in the search included: "autonomous vehicles", "self-driving cars", "machine learning", "deep learning", "vision neural networks", "elderly users", "aging population", "senior citizens", "accessibility", "trust and acceptance", "cognitive challenges", “human-computer interaction”.

3) *Search syntax:* Boolean operators (AND, OR) were used to combine search terms and refine the search results. For example, the search string "autonomous vehicles AND machine learning AND elderly users" was used to identify studies that specifically addressed the intersection of these topics.

4) *Timeframe:* The search had a time limited for each article. They must have been published between January 2020 and August 2024 to ensure the inclusion of the most recent research.

### C. Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were established to ensure that the studies selected for the review were relevant and of high quality. The criteria are as follows:

1) *Inclusion Criteria*

*a)* Studies that focus on autonomous vehicles and their application to the aging population.

*b)* Research involving machine learning and vision neural networks in the context of AVs.

*c)* Empirical studies, including quantitative, qualitative, and mixed-methods research.

*d)* Review journal articles, conference papers, and academic journals.

*e)* Publications in English to ensure accessibility and comprehension.

2) *Exclusion Criteria*

*a)* Studies not related to the aging population or elderly users in the context of AVs.

*b)* Articles that do not involve machine learning or vision neural networks.

*c)* Non-empirical studies, such as opinion pieces, editorials, and commentaries.

*d)* Publications not available in English or some lacking full-text access articles.

### D. Data Extraction and Analysis

Data extraction and analysis were conducted systematically to ensure accurate and comprehensive synthesis of the literature. The following steps were undertaken:

*1) Data Extraction*

*a)* A standardized data extraction form was developed to capture key information from each selected study. The form included fields for:

*i)* Study title, authors, and publication year.
*ii)* Research objectives and questions.
*iii)* Methodology and study design.
*iv)* Sample characteristics and size.
*v)* Key findings and conclusions.
*vi)* Implications for AV design and implementation for the aging population.

*2) Data synthesis*

*a)* The extracted data were synthesized because the goal of identifying commonalities is to among themes, trends, and gaps in the literature. Thematic analysis has been done on the categorized findings around certain topics like accessibility, trust, cognitive challenges, and technology acceptance.

*3) Identifying key themes and trends*

*a)* Based on the study, the critical themes and trends in the literature are the role of machine learning in enhancing AV accessibility for the elderly, the impact that visual neural networks have on user experience, and factors influencing trust and acceptance among older adults.

*4) Reporting the results*

*a)* It shows the current research stage, research gaps, and possible directions for future studies in this area. The results will be useful to inform the design and development of AVs that are accessible and user-friendly for the aging population.

*5) Quality assessment*

*a)* Although scoping reviews generally do not involve a formal quality assessment, the studies identified were assessed with respect to methodological rigor and relevance to ensure the strength of the findings.

## III. FINDINGS

### A. Overview

A comprehensive search obtained by computer was conducted across in four major databases which are PubMed, IEEE Xplore, Scopus, and Google Scholar. As a result, there was a total of 5,702 articles (with 19,300 results from Google Scholar) has been yielded. Also, there were 158 articles were obtained by manual retrieval of references of included articles. A total of 732 articles were eliminated by EndNote20 software and manual deduplication. After reading the title, 4,969 articles that obviously did not meet the research theme were eliminated. After reading the abstract and combining the inclusion and exclusion criteria, 701 articles were excluded. Finally, 31 articles were included [13-43]. The literature screening process of this study is shown in Fig. 1. All selected journal articles explored the integration of machine learning and vision neural networks in autonomous vehicles (AVs) with a specific focus on the aging population. The geographical distribution of the studies included North America (8 studies) [14] [20] [23] [24] [25] [26] [30] [38], Europe (8 studies) [16] [17] [22] [29] [31] [32] [37] [41], Asia (13 studies) [15] [18] [19] [21] [28] [33] [34] [35] [36] [39] [40] [42] [43], and other regions (2 studies) [13] [27]. Please refer to Fig. 2 for details.

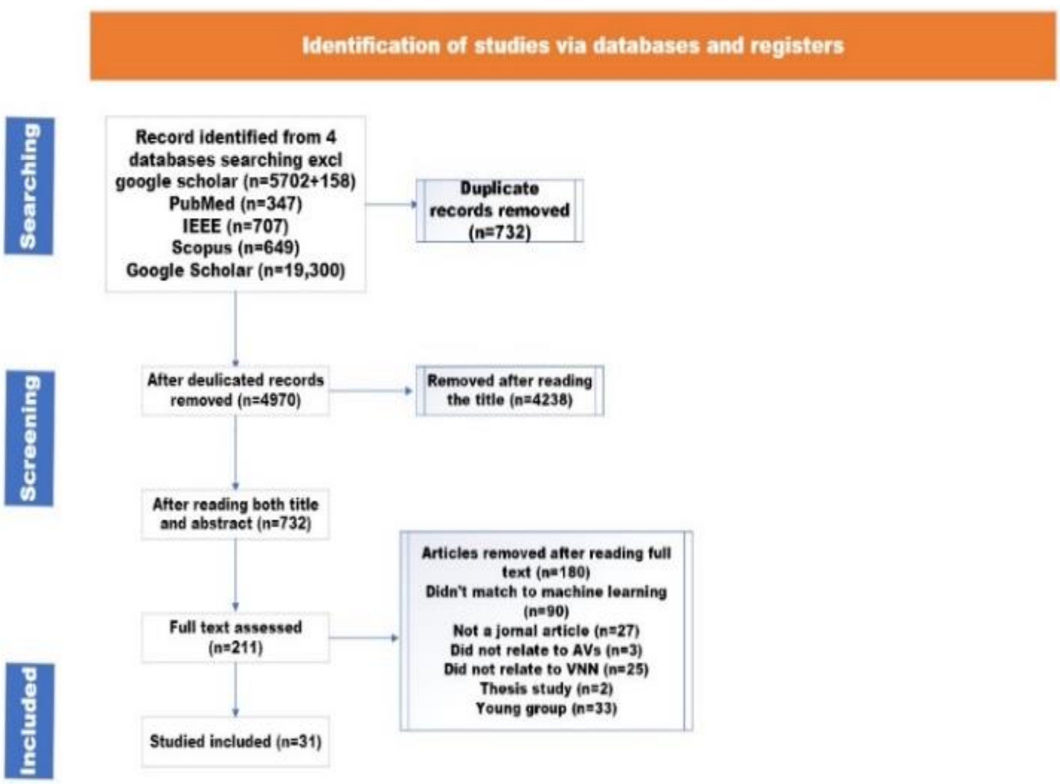


Fig. 1. Flow chart of literature screening.

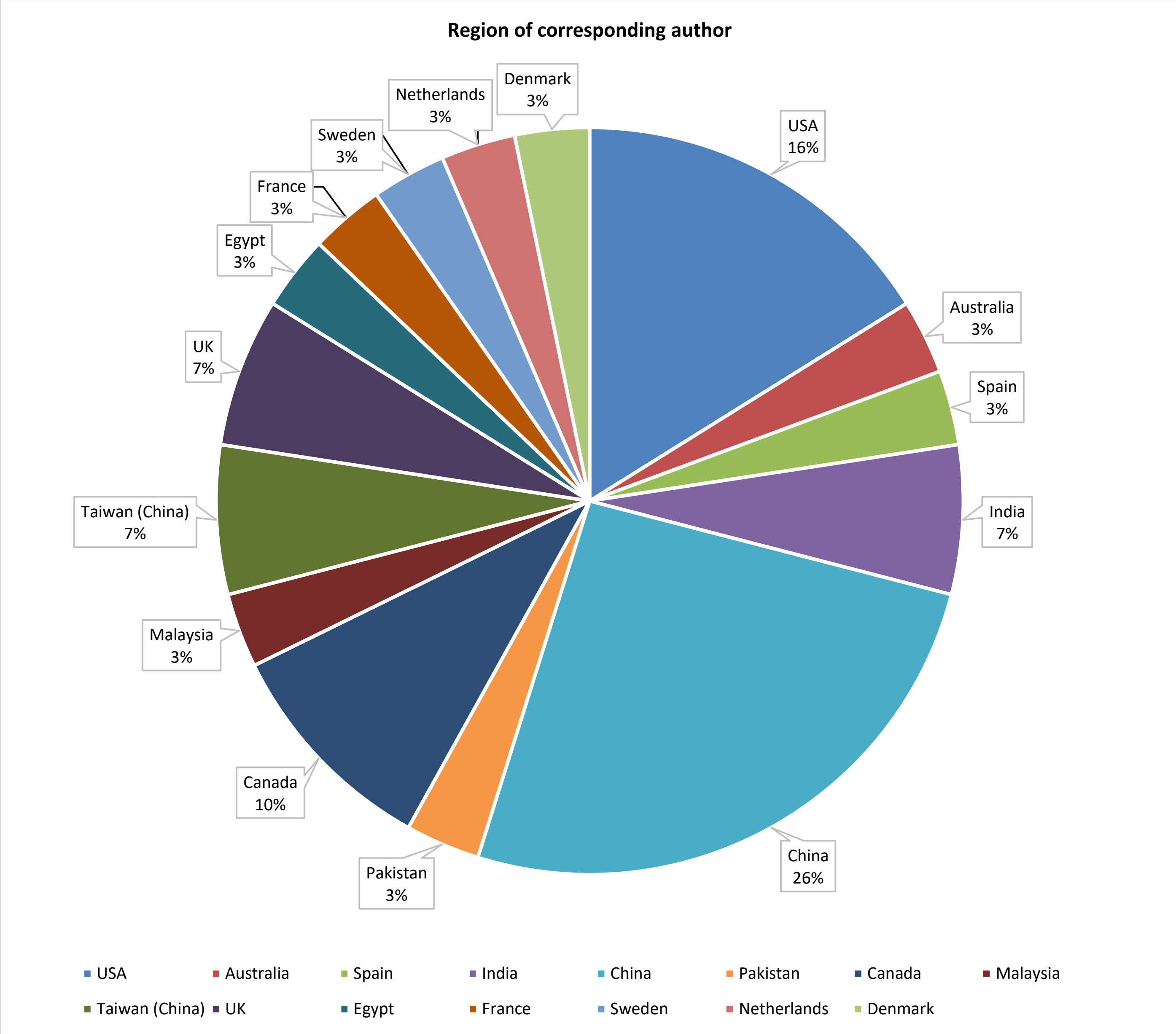


Fig. 2. Chart of articles' geographical distribution.

### *B. Sample Characteristics*

The reviewed studies included diverse sample sizes and participant demographics. Of the 31 studies, 15 involved human participants, with a particular focus on elderly and disabled individuals [16] [19] [20] [22] [24] [25] [26] [27] [29] [31] [32] [34] [38] [42] [43]. The sample sizes in these studies in a range from 50 participants to 3,500 participants. Those with larger sample sizes were typically sourced from national health surveys and electronic health records (EHRs) which are over 1000 participants. The remaining 16 studies utilized simulation environments and predictive models to examine interactions between AV systems and various user groups. Many studies highlighted the importance of large, diverse datasets to properly train machine learning models, especially to cater to the needs of underrepresented groups.

### *C. Types of Machine Learning Algorithms*

The studies employed various machine learning algorithms to enhance AV functionality and safety for elderly and disabled users. The most commonly used method was Tree-based methods. It's including Random Forest and Gradient Boosting Machines (GBM). There were about in 12 studies appeared [14] [29] [32] [40]. These algorithms were preferred for their robustness in managing complex datasets. There were seven studies mentioned Neural networks, this included Convolutional Neural Networks and Recurrent Neural Networks [14] [15] [32] [39] [40]. The primary use for vision-based tasks like object detection and predicting user behavior. Support Vector Machines (SVMs) and Bayesian Networks were featured in five studies [14] [19] [29] [32] [42], particularly for predicting user trust and acceptance of AV technology among elderly users (Fig. 3).

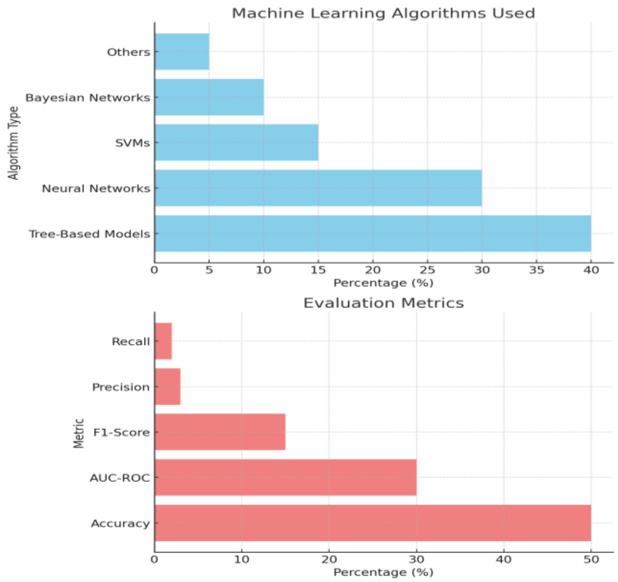


Fig. 3. ML algorithms used & evaluation metrics.

### D. Handling of Missing Data

Handling missing data was a key focus in several studies due to the complexity and diversity of the datasets involved. Of the 31 studies, nine specifically discussed their strategies for dealing with missing data. Multiple imputation was the most commonly used technique, which reported in five studies. On the other hand, there were four studies used k-Nearest Neighbors. These methods were critical for maintaining dataset integrity, especially in studies involving health data or surveys where missing values were prevalent.

### E. Evaluation Metrics and Model Performance

The studies used a variety of metrics to evaluate the performance of machine learning models in AV systems. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was the most frequently reported metric, used in 14 studies, to assess the models' ability to distinguish between successful and unsuccessful AV operations involving elderly and disabled passengers. Calibration plots and Brier scores were also used in 6 studies to evaluate the accuracy of predictive models [25]. The average AUC-ROC across the studies was approximately 0.84, it was indicating a high level of accuracy. However, the calibration scores varied. Only 18% of the studies reporting well-calibrated models, which means it requires for further improvement.

### F. Trust and Acceptance Among Elderly and Disable Users

The Trust and acceptance of AVs among elderly and disabled users were key themes in 14 of the studies reviewed [19] [20] [22] [23] [24] [25] [26] [30] [31] [41] [43]. These included questionnaires, behavioral experiments, and physiological data. These studies took various methods to measure trust like surveys, behavioral experiments and physiological measurements (heart rate and skin conductance). The outcomes of the studies consistently indicated that trust in AV technology was influenced by these factors:

1) The transparency of the AV's decision-making processes.
2) The predictability of the vehicle's behavior.
3) The perceived safety of the system.

Studies that integrated user feedback mechanisms into the machine learning models showed a significant improvement in trust by allowing the AV systems to adapt to individual user preferences. However, some people concerned about the potential for reduced situational awareness due to overreliance on automation, particularly among elderly users.

TABLE I. TYPES OF MACHINE LEARNING ALGORITHMS USED

| Trust and Acceptance Factor | Number of Studies |
|---|---|
| Transparency of decision-making processes | 14 |
| Predictability of vehicle behavior | 14 |
| Perceived safety of the system | 14 |
| User feedback mechanisms | 10 |
| Concerns about reduced situational awareness | 8 |

### G. External Validation Bias Assessment

External validation of the machine learning models was reported in 7 of the 31 studies. These validations were conducted using independent datasets, aims to test the generalizability of the models' performance. The studies that included external validation generally reported good performance, with AUC-ROC scores consistent with those obtained during internal validation. However, in the majority of studies had the lack of external validation seems like a limitation. Users may have their concerns about the models' applicability in real-world settings. Bias assessment was addressed in 19 studies (61%), with common sources of bias being related to data collection. Especially the underrepresentation of certain demographic groups such as elderly groups and disable groups. The studies emphasized the need for more inclusive datasets to ensure that AV systems are designed to meet the needs of all users.

### H. Summary of Key Findings

The findings from this scoping review indicate that significant progress has been made in applying machine learning, human-computer interaction principles, and vision neural networks. They all aim to improve the safety and usability of autonomous vehicles for diverse populations. Groups of elderly and disabled individuals were included. Vision neural networks, like those used in Tesla's current technologies, have proven essential in tasks such as object detection, road sign recognition, and pedestrian behavior prediction. These advancements have significantly made the accuracy of AV systems improved in real-world scenarios.

There are still a few challenges remain: The problems are in the areas of data quality, model validation, and user trust. Although machine learning models (including vision neural networks) have demonstrated high accuracy in controlled environments, their real-world applicability is still limited by issues. Such as data bias and the need for external validation. The integration of these advanced machine learning techniques into AV systems holds significant promise for enhancing mobility and independence among elderly and disabled individuals.

Further research is addressing the identified gaps. The key focus of fields will be in developing models that are robust, inclusive, and capable of gaining the trust of all users. Future studies should focus on improving data collection methods, increasing transparency in AV systems, and ensuring that models, including vision neural networks, are validated across diverse populations and environments.

## IV. Discussion

The integration of machine learning and vision neural networks in autonomous vehicles (AVs) represents a significant leap forward in enhancing the safety, usability, and overall functionality of these technologies for diverse populations, particularly elderly and disabled users. This discussion delves into the implications of the findings, addressing the potential benefits, existing challenges, and areas for future research and development.

### *A. The Promise of Machine Learning and Vision Neural Networks in AVs*

Machine learning algorithms, particularly those involving vision neural networks, have shown substantial potential in improving the decision-making processes of AVs. Vision neural networks enable AVs to accurately interpret visual data from the environment, facilitating real-time object detection, road sign recognition, and navigation in complex driving conditions [44] [7]. These capabilities are especially beneficial for elderly and disabled users who may face physical or cognitive limitations that impact their driving abilities [45] [46].

The findings of this review highlight the importance of these technologies in creating AV systems in both functional and inclusive. By addressing the specific needs of elderly users, such as reducing cognitive load and enhancing the predictability of vehicle behavior, machine learning models can significantly improve user trust and acceptance of AV technologies [47] [48].

### *B. Challenges in Data Quality and Model Validation*

Despite the advancements, the review also underscores several challenges that need to be addressed to fully realize the potential of machine learning and vision neural networks in AVs. One of the primary concerns is data quality. Many studies pointed out the issues related to the underrepresentation in the datasets used to train these models. Especially in the certain demographic groups such as minorities or individuals with specific disabilities [49] [50]. This underrepresentation can lead to biased algorithms that may not perform as effectively across diverse populations [51].

Moreover, less external validation in many studies raises concerns about the generalizability of these models. The internal validation results are promising, but the models need to be tested on independent datasets. This is to ensure they can operate reliably in varied real-world conditions [45] [52]. Without this external validation, there is a risk that the models could fail when exposed to scenarios not covered in the original training data.

### *C. Trust and Acceptance Among Elderly Users*

Trust plays a crucial role in the acceptance of autonomous vehicles (AVs), particularly among elderly users. Several studies highlight that trust, alongside transparency and perceived safety, significantly impacts how older adults interact with AV technologies [53] [54]. Machine learning models that incorporate user feedback have shown promise in enhancing trust, allowing AV systems to adapt to the specific comfort levels and preferences of elderly users [55].

However, concerns about overreliance on automation remain, with many highlighting the potential reduction in situational awareness. Maintaining a balance between offering assistance and ensuring users remain engaged is critical to preserving both safety and trust [56]. Trust-building in AV technologies requires transparency and real-time communication to help elderly passengers calibrate their trust levels accurately [54].

### *D. Future Research Directions*

Further research is needed to optimize machine learning and vision neural networks in AVs, especially for elderly and disabled users:

1) *Personalization and adaptability:* Future work should focus on creating adaptable systems that cater to individual preferences, thus reducing cognitive load for elderly users [57].

2) *Inclusive data collection:* Researchers must ensure datasets used for training AV models include diverse user groups to mitigate biases and improve model generalizability across various populations [58].

3) *Ethical and regulatory frameworks:* As AV technologies evolve, regulatory frameworks must address ethical concerns, such as data privacy and algorithmic bias, to ensure AV systems remain fair and accessible [59].

4) *Longitudinal studies on trust:* Conducting long-term studies to track how elderly users interact with AVs can provide valuable insights into trust dynamics and safety improvements [60].

### *E. Implications for Industry and Policymakers*

Industry stakeholders must prioritize the design of AVs that are accessible and user-friendly for elderly and disabled individuals. Investment in machine learning models that adapt to diverse user needs will be essential for broad adoption of AV technologies [61]. Additionally, policymakers should focus on creating regulatory frameworks that support the ethical development of AVs. The reason is ensuring the benefits of these technologies are equitably distributed [59].

## V. Conclusion

This scoping review highlights the significant role that machine learning and vision neural networks are playing in advancing autonomous vehicle (AV) technology, particularly in addressing the needs of the aging population. These technologies make AVs to process vast amounts of data in real-time. Therefore, it's allowing for safer and more efficient driving experiences. The application of vision neural networks has improved the ability of AVs to recognize and react to objects, traffic signals, and dynamic environments in particular, making them especially useful for elderly users who may face cognitive and physical limitations. By incorporating adaptive interfaces and assistive features, these technologies can enhance user trust, acceptance, and overall mobility, helping elderly individuals maintain their independence longer.

However, these advancements haven't achieved everything. There are still several critical challenges which need to be addressed to fully optimize AV systems for elderly populations. This scoping review revealed concerns about data quality. The underrepresentation of older adults and individuals with disabilities in datasets used for training machine learning models especially. This underrepresentation could lead to biases in the system, which may result in reduced safety and reliability for these specific user groups. Additionally, there is a limitation of external validation for many models after reviewed the articles. The raising questions about their generalizability and performance in diverse, real-world conditions.

Trust remains a key issue for the adoption of AV technology by elderly users. As AV systems become more automated, the potential for overreliance and reduced situational awareness poses a risk, especially for older adults who may already have diminished cognitive abilities. Ensuring that AV systems provide transparent and reliable feedback and allowing users to maintain a level of control when needed, is critical for building trust. Future research should prioritize developing machine learning algorithms/vision neural networks technology that can adapt to the unique cognitive and physical requirements of elderly users. The ethical concerns such as data privacy and inclusivity will also be considered.

It is essential to improve the inclusiveness of data collection efforts as the solution to resolve these challenges. The machine learning models are externally validated across diverse populations at the same time. Regulatory frameworks must evolve to address the ethical considerations surrounding AV technologies. This will include fairness, algorithmic bias, and transparency in decision-making processes. As It's particularly important as AV technology moves towards broader implementation, where ensuring accessibility for all user demographics is vital.

At present, there is a lack of interactive systems, machine learning, and visual neural network functions designed specifically for the elderly and disabled. The integration of personalized AV systems that cater specifically to the needs of elderly (as well as disabled individuals) will be essential in the coming decade to ensuring the widespread acceptance and success of AV technology. By focusing on user-centric designs which the area of HCI will exert power and continuing to improve the robustness of machine learning models. As a result, AVs with these new functions have the potential to improve the mobility, independence and quality of life for elderly populations. Policymakers, researchers and industry stakeholders must collaborate together. Their collaboration is the key of inclusive, reliable, and capable in autonomous vehicle technology. Ensuring it is reliable for the full spectrum of users' needs.

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