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Global distribution and readiness status of artificial intelligence application on mobility projects

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Abstract

The mobility sector is experiencing a global transition towards cleaner and more sustainable technologies. Many mobility projects are developing artificial intelligence (AI) technologies to improve the operational efficiency of mobility, such as charging system optimization for electric vehicles (EVs), autonomous driving, and traffic controls. This study presents such projects' global distribution by showing a geographic information system (GIS)-generated map and analyzes the readiness level of those technologies by employing the Japanese Technology Readiness Assessment (J-TRA) methodology. The results show that most projects are located in Europe. Among the analyzed AI uses, the smart parking system and lane tracing assistance technologies have the highest level of readiness. Further training of AI to be fully compatible with the real operating environments and updates of traffic policies are necessary to allow advancement of the technology readiness of the rest of AI mobility technologies types.

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Keywords: Artificial intelligence; Electric vehicle; Technology readiness; TRA; GIS

1. Introduction

Air pollution in large cities has caused the need for a sustainable transportation system in urban areas. It is estimated that electric vehicles (EVs) can reduce air pollution and greenhouse gas emissions by 21% by 2050 [1]. The development of EV technology has progressed significantly over the last few years. It has contributed to the transition towards clean transportation. Many countries work on leveraging EV adoption by providing compatible infrastructure and supporting policies [2]. Although EV technology is mature [3], it is vital to investigate and assess how artificial intelligence (AI) can increase the efficiency of EVs and improve environmentally friendly mobility

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to grasp and leverage the full potential of the most recent innovations. Governments and industries worldwide are working hand-in-hand to develop AI technologies to improve EV operations and traffic and increase the performance and efficiency of machines, system processes, and human–machine interactions [4]. In the case of EVs, AI technology integration is used for energy management, such as charging systems optimization, autonomous driving technology development, and traffic control management [5,6].

Many researchers have noticed that one barrier to EVs for energy management is the limited charging infrastructure and battery lifetime [7]. To overcome this challenge, vehicle-to-grid (V2G) technology has been developed to allow bidirectional energy exchange between electric cars and the power grid and advance the role of EVs as a solution for green transportation. Tan et al. [8] proposed an optimization algorithm to improve the V2G system by considering different objectives, such as cost, emission, profit, power loss, and other variables. Similar research was also conducted by Hu et al. [9], exhibiting efforts on battery modeling, communication, charging standards, and driving patterns using AI to solve the optimization problem. Furthermore, V2G charging scheme optimization using a genetic algorithm was studied by Al-Nahid et al. [10]. Aside from V2G technologies, AI has also been used to optimize the charging station location based on EV driving range, as studied by [11–13], and [14].

AI technology is also used for autonomous or self-driving vehicles. While most studies about self-driving vehicles did not specify the vehicle's type of engine, it is commonly applied on EVs as sensors and other parts require electricity to operate. The neural network is the most commonly used method for developing a self-driving vehicle, as suggested by [15,16], and [17]. Using neural network AI technology, EVs' capability to assess the environment and make driving judgments can be enhanced. A study by Nie and Farzaneh [18] shows the capability of AI, including machine learning, to control EVs considering real-time traffic data and signal information. Xue and Jiao [19] proposed a speed adaptive control for hybrid EVs to ensure that the controller can ensure solid and secure vehicle-following performance despite varying vehicle acceleration and road slope. Qi et al. [20] applied reinforcement learning to enhance a hybrid electric vehicle's capability to study its surroundings as part of its energy management.

Moreover, as the number of commercialized electric vehicles (EVs) increases, research on AI-based traffic management technology has been conducted. Li et al. [21] applied energy management based on deep reinforcement learning in networked traffic. The EV's energy management strategy includes a deep deterministic policy gradient method to design the vehicle's reference speed. At the most fundamental level of AI application, a driver model and adaptive equivalent consumption reduction approach execute optimal power split control based on the anticipated reference speed. Shi et al. [22] proposed EV traffic control management systems that use real-time traffic data to optimize energy-use efficiency. Wang et al. [23] proposed an optimization model for EV traffic management by considering en-route charging location detection.

In addition to academic research, many countries that have successfully adopted EVs have begun to pursue project-based AI. The present study displays the distribution of such technology development worldwide by the geographic information system (GIS)-generated maps and analyzes the readiness level of those technologies conducting technology readiness assessment using the Japanese technology readiness assessment (J-TRA) methodology. First, we developed a mini database of AI integration for EV projects. We categorized the information based on the kind of AI used, funding mechanisms, project type, size, and readiness level. Second, we analyzed the seven readiness parameters of the J-TRA methodology: (1) market, (2) technology development, (3) system integration, (4) sustainability verification, (5) safety, (6) commercialization, (7) cost, and risk. The outcome of this research is a better understanding of the present state of AI application readiness on electric vehicles (EV) and identifying the impediments to speeding the development of AI on the EV technology readiness level (TRL).

2. Materials and methods

This study developed a mini database of projects that apply AI technologies to EVs. The data were searched from government-funded project database websites such as the European Commission's inventory on AI projects for mobility [24], the Japanese Ministry of Environment (MOE)'s repository of funded technology demonstration project reports [25], and private company websites using the search keywords "artificial intelligence", "electric vehicle", "smart mobility", "autonomous vehicle", and "self-driving car". We gathered data from 50 locations and classified them into the type of AI use, funding mechanisms, and general readiness status.

We analyzed the data with descriptive statistics to show the general trends, and then we plotted the locations of technology development projects with a GIS. We also analyzed the readiness level of each identified technology by employing the J-TRA methodology. Fig. 1 summarizes the research framework of this study.

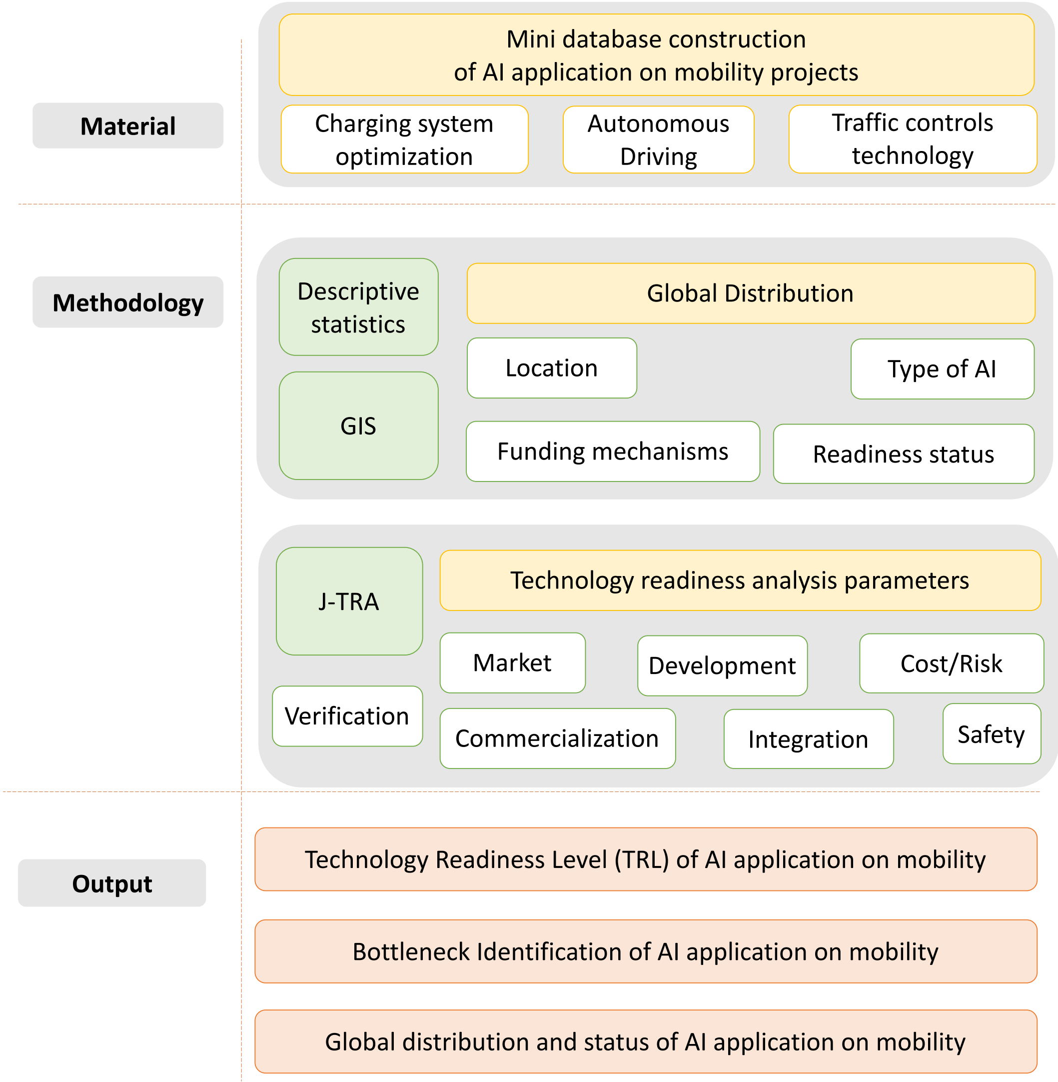

Fig. 1. Research framework.

2.1. The J-TRA methodology

The technology readiness assessment (TRA) method was first developed by the national aeronautics and space administration (NASA) in the 1980s [26]. The methodology was intended to find gaps in testing, demonstration, and the general knowledge of technology to identify the required steps to enhance the technology's readiness status. The method contains a systematic, metric-based process that assesses and reports the maturity of a specific technology used in various systems [27]. The methodology was so robust that it was used outside the field of aeronautics and the United States (US) [7,28–30]. The Japanese MOE adapted the TRA for government-funded technology demonstration projects and polished the methodology based on feedback from technology developers over three years [26]. Based on the feedback, social parameters such as market and commercialization were added to the methodology, as they were not represented enough in the original version [26].

The J-TRA contains seven parameters for readiness assessment: (1) market, (2) technology development, (3) system integration, (4) sustainability verification, (5) safety, (6) commercialization, and (7) cost and risk. Each of the parameters has a compliance checklist to determine the readiness status of the technology. The compliance checklist is accessible from the manual published by the Japanese MOE [31]. Therefore, three calculation stages must be conducted to calculate the technology readiness level (TRL) score. First, as the present study tries to understand the global status of AI use, particularly for three technologies: (1) Charging System Optimization, (2) Self-driving car Technology, and (3) Traffic Control Technology, the average score is taken as expressed by Eq. (1). Then, because the length of the checklist of each parameter is different, a normalization step is required (Eq. (2)). Finally, the technology bottleneck is identified by the lowest score of the TRL (Eq. (3)).

$$X_{j,k} = \frac{\sum_{i}^{n} X_i}{n} \tag{1}$$

$$N_k = \frac{X_{j,k}}{Max_k - Min_k} \times 100\% \times 8 \tag{2}$$

$$TRL_j = Min_{Nk} \tag{3}$$

$X_{j,k}$ represents the mean value of global scores of technology j for parameter k, and N_k represents the normalized value for parameter k. The maximum value of parameter k or Max_k and the minimum value for parameter k or Min_k can be identified by the alphabet–numeric combination codes in the J-TRA scoring matrix accessible from [26]. The fixed value, 8, in Eq. (2) refers to the maximum TRL score.

In level 8 of TRL, the technology has achieved its full readiness, which means it is safe to use, fully functional in its intended environment, fully integrated into the surrounding infrastructure, complies with energy efficiency standards, and is widely used in the market. On the other hand, the TRL of technology j or TRL_j takes the lowest normalized value (Eq. (3)) because the goal is to highlight the bottleneck. For example, it is possible that although technology is fully developed, it is stuck on a pilot demonstration status due to commercialization challenges. Such results can warn decision-makers and encourage them to take commercialization actions to let the readiness status progresses upward.

3. Results and discussions

3.1. Global distribution of artificial intelligence applications on electric vehicles

Fig. 2a and b show the distribution of technology development projects by location and readiness levels. A self-driving car or autonomous driving technology is the most popular technology developed and tested globally. Most of the projects are in Europe and Asia, with Germany leading in Europe and Japan leading in Asia. These two countries are known for long-term global car producers such as Toyota, Mazda, Volkswagen, and Daimler. Regarding the balance of technology types developed, Europe seems to be more well-round than its Asian counterparts. This is mainly because Europe is determined to make a complete transition to EVs. On the other hand, Japan has an equally prioritized green hydrogen technology development plan to achieve the carbon neutrality goal in the transportation sector [2,32]. The US has fewer projects, but they are among the highest readiness levels, with some technologies having reached near commercialized and mass production levels. While European and Japanese projects are mainly under public–private-partnership funding mechanisms, American projects are commonly funded by the private sector only, such as Tesla [33] and Google [34].

Regarding readiness levels, traffic control technology is the most diverse because there is a diversity in the type of traffic control being developed. For example, European cities such as Geneva have a smart parking system to reduce traffic congestion by helping drivers find free parking spots nearby. This technology has already reached mass production readiness levels and is being widely implemented in other European and Asia Pacific countries [35]. In addition, smart traffic lights in Copenhagen, Denmark, are managed by AI to prioritize public transportation over private passenger cars, and cyclists do not have to stop at traffic lights [36]. This technology is still at a pilot level but effectively drives people's preference for the least polluting mobility choice. On the other hand, focusing on self-driving car technology is common for crash avoidance, especially during severe weather conditions [37,38].

The locations of AI applications on mobility projects are plotted on ArcGIS's map shown in Fig. 3. Based on the limited database constructed for this mini-study, Europe leads with 25 project locations. Some European cities have multiple projects, such as Sindelfingen, Wolfsburg, and Aachen, the headquarters and research and development centers of major car makers in Germany. Japan has test sites for green slow mobility demonstration projects scattered in several towns and cities [25], namely, Kotohira town in Kagawa prefecture, Onomichi city in Hiroshima, and

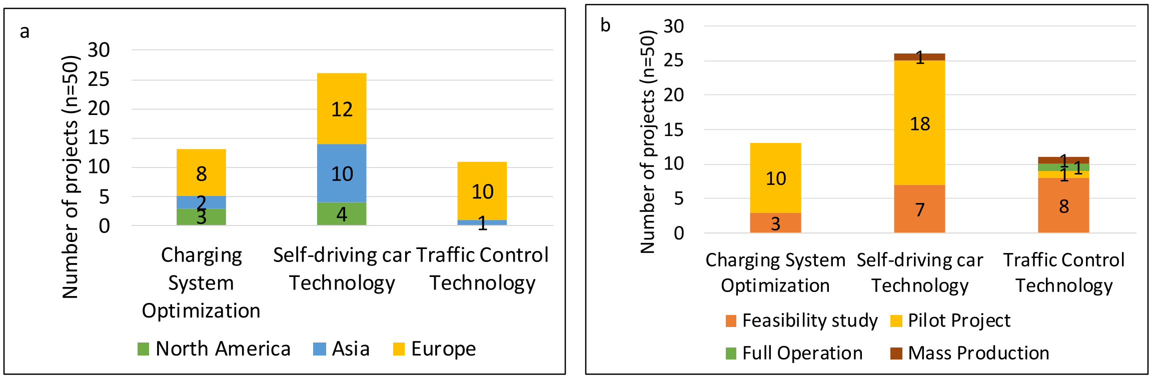

Fig. 2. Global AI application on mobility projects: (a) by location, (b) by readiness level.

Fig. 3. Global distribution of AI applications on mobility projects.

Iiate village in Fukushima. Towns with smaller population densities are generally selected as the testing areas. Japan has a serious problem of declining income from tourism, depopulation, and an aging society. Some public facilities, such as train and bus services, had to be modified or stopped due to a lack of passengers [39]. Such a phenomenon might be the reason for the PPP-funded development of a fully autonomous vehicle where the presence of a driver is not required to operate the vehicle. On the other hand, the autonomous driving technology developed by the private sector assists drivers in making the driving experience safer and more efficient, such as lane tracing assistance [40]. Such technologies are on high readiness levels as they are available commercially.

3.2. J-TRA results

Because many AI technology development projects for mobility are supported by the private sector, either fully or partially in the form of a consortium or a PPP mechanism, there is usually already an established market that is the preexisting consumer of commercial passenger cars. On the other hand, innovative business models, such as Tesla's smartphone application-based ride-hailing system currently serving users in Phoenix, Arizona [41], are being tested. Therefore, with a clear market demand and supply chain, the market parameter has the highest readiness level among the J-TRA parameters (Fig. 4).

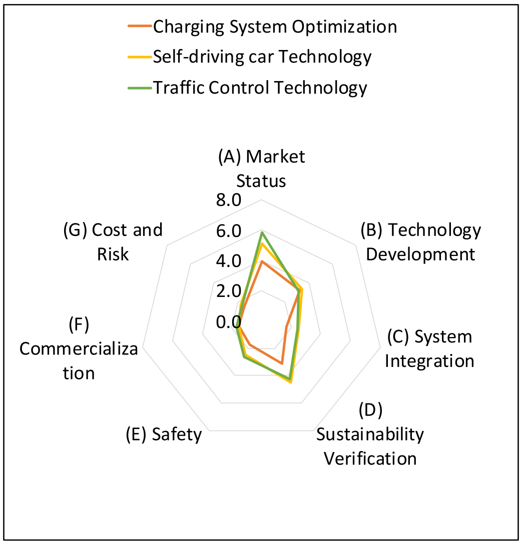

Fig. 4. TRL of AI use for mobility technologies.

Technology development is among the most challenging areas for AI applications on mobility because the technology is still relatively new. Many variables relating to uncertain environmental conditions must be integrated to train the AI to be fully functional. Moreover, the new technology has to integrate into the current system by changing the infrastructure or making technology compatible with the existing infrastructure. Safety, costs, and risks are all related to policy compliance and countermeasures for accident prevention, which may require some time to test and adjust. A new policy from the government side may also be needed, as some may not apply to newly developed technologies.

Verification of the sustainability parameter, however, has already progressed to quite advanced status, as the technology is about improving the efficiency and effectiveness of energy use for mobility and reducing driving time.

4. Conclusion

As the transportation sector contributes a significant amount of GHG emissions to the environment, efforts to make mobility more efficient with AI are important to aid the mitigation of climate change. Governments and the private sectors are developing AI-based mobility technology in three major sectors: charging system optimization, autonomous driving, and traffic control technologies. The mini global database of AI applications on mobility projects built in this study showed that Germany is leading in Europe and Japan is leading in Asia regarding the number of demonstration projects being conducted. The finding is not surprising because these countries are the leading car manufacturers and there is significant support from the government. While Japan focuses on autonomous driving to boost tourism and solve aging and depopulation mobility challenges, European projects handle more diverse sectors, including smart parking and smart traffic lights, to drive people to use more sustainable means of transportation. Regarding readiness levels, the bottleneck of the technologies commonly lies in further training AI to perform in an actual environment where there are highly diverse and changeable factors. Furthermore, policies should be updated to accommodate new sustainable and efficient mobility methods.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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