

Article

Identification of Key Core Technologies and Competitive Landscape Analysis for Intelligent Vehicles Based on Patent Data

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Abstract

Intelligent vehicles represent a frontier in technological innovation. Effectively identifying their key core technologies and primary competitors is a crucial prerequisite for overcoming industrial technological bottlenecks, playing a pivotal role in promoting sustainable industrial development and enhancing global market competitiveness. This study is based on 46,373 authorized invention patents in the field of intelligent vehicles from 1950 to 2024 and based on four core characteristics of key core technologies: technological centrality, technological value, economic value, and competitive monopoly. Combining the entropy weight method and gray correlation analysis method, it effectively identifies 15 key core technologies in the field of intelligent vehicles, including G05D1, B60W30, G08G1, etc. These technologies cover four core domains: autonomous driving and vehicle control, intelligent transportation and vehicle–road coordination, onboard computing and data processing, and powertrain system integration and optimization. Building on this foundation, the study analyzes the technological competitive landscape from both national and corporate perspectives. The results show that the United States and Japan, with their profound technological accumulation, demonstrate strong competitive strength. China leads globally with 25.56% of worldwide patents, exhibiting rapid growth in R&D scale. However, the technological influence of key core technology patents held by major Chinese enterprises still lags significantly behind that of the United States and Japan, indicating room for improvement in R&D quality. By precisely identifying core R&D directions for intelligent vehicles, this study provides strategic guidance and practical references for optimizing green innovation resource allocation within the industry. It aims to overcome key technological bottlenecks in low-carbon intelligent vehicles, thereby achieving breakthroughs in key core technologies and enabling high-quality, sustainable industrial development.

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1. Introduction

Today, intelligent vehicle technology is flourishing. As a model of high-tech integration, it is progressively driving profound transformations in mobility patterns and comprehensive restructuring of transportation systems [1]. Intelligent vehicles are not only

the core driving force behind industry advancement with immense application potential, but also a strategic high ground for global emerging industrial development and transformation. Their technological breakthroughs and industrial implementation directly propel the intelligent and low-carbon upgrade of urban mobility, serving as a key enabler for achieving sustainable urban transportation and transitioning to low-carbon transport systems. This aligns closely with the United Nations Sustainable Development Goals and national green transportation strategies, embodying both industrial value and ecological sustainability.

Intelligent vehicles refer to next-generation automobiles that gradually evolve into smart mobility spaces and application terminals. Equipped with advanced sensors, controllers, actuators, and other devices, and integrating modern communication and network technologies, these vehicles possess control functions such as information sharing, complex environmental perception, intelligent decision-making, and automated coordination. They enable information exchange with road infrastructure and cloud platforms, forming intelligent transportation systems [2]. Intelligent vehicles are also commonly referred to as intelligent connected vehicles or autonomous vehicles. China has made significant strides in key technologies for intelligent vehicles, yet practical challenges persist, including insufficient innovation in key core technologies and room for improvement in international competitiveness. As an emerging high-tech industry emerging from the backdrop of a new technological revolution, the development of intelligent vehicles heavily relies on breakthroughs and innovations in core technologies [3]. Therefore, effectively identifying key core technologies and understanding their competitive landscape is a crucial prerequisite for defining the primary focus areas within an industry sector. This holds significant practical and strategic value for enhancing industrial competitiveness, driving the coordinated development of the entire industrial chain—including new energy, intelligent transportation infrastructure, and green mobility services—and ultimately optimizing the allocation of innovation resources in the national intelligent vehicle sector. It lays the technological foundation for achieving long-term green and sustainable development in the transportation sector and enabling high-quality industrial upgrading.

Although existing research has explored patent analysis and technology identification in the intelligent vehicle sector, further investigation is warranted. First, current studies often focus on single-dimensional patent metrics when identifying key core technologies [4], with few adequately considering their multifaceted characteristics. The comprehensiveness and objectivity of identification results require improvement. Second, differing research perspectives make direct comparison and synthesis of findings challenging. There is a need to clearly define the key core technologies specific to the intelligent vehicle domain and conduct corresponding analyses of their development trends and competitive landscapes. Third, much existing research on intelligent vehicles emphasizes improvements to specific technical algorithms [5], with few studies offering holistic analyses of the industry's technological development trajectory or providing actionable recommendations for industrial advancement.

Based on these research gaps and industrial development needs, the core objectives and research questions of this study are defined as follows:

1. Develop a multidimensional, objective identification framework for intelligent vehicle core technologies based on their key characteristics, enabling precise identification of core technology types and their distribution across technical domains;
2. Combine identification results with a dual-perspective analysis (national and corporate) to quantitatively assess the global competitive landscape of intelligent vehicle core technologies, clarifying the competitive strengths and weaknesses of each stakeholder;

3. Integrate the identification results and competitive landscape analysis to provide strategic guidance for the national intelligent vehicle industry to overcome core technological bottlenecks, optimize the allocation of green innovation resources, and achieve high-quality sustainable development.

This study focuses on the intelligent vehicle industry, utilizing 46,373 granted invention patents in the field from 1950 to 2024 as its data source. It constructs a multidimensional comprehensive identification index system based on four key characteristics: technological positional core, technological value, economic value, and competitive monopoly. By integrating the entropy weight method and gray correlation analysis, the study quantitatively identifies core technologies in the intelligent vehicle sector and conducts an in-depth analysis of the global technological competitive landscape from a worldwide perspective. The research findings can serve as a reference for nations and enterprises to evaluate their strengths and weaknesses in key technology domains and knowledge sources. This enables optimized allocation of green innovation resources, identification of technological innovation opportunities, and formulation of precise and efficient technological and market strategies. Ultimately, it aims to seize the initiative in intense global competition, driving technological innovation and the high-quality, sustainable development of the intelligent vehicle industry.

2. Related Research

2.1. Definition and Characteristics of Key Core Technologies

Currently, scholars have not reached a unified definition of the concept of key core technologies. However, it is widely recognized that key core technologies occupy a central position within a technological system and play a critical role. They require long-term, high-intensity R&D investment, exhibit complexity and difficulty in substitution [3], exert significant influence on industrial development, and possess substantial economic value [4]. This paper defines key core technologies as technical systems designed and constructed by specific entities, occupying a central position within their respective industrial technology ecosystems, playing a critical role, being difficult for other entities to imitate or master in the short term, and possessing complexity, scarcity, exclusivity, and significant economic value.

Summarizing existing research, the primary characteristics of key core technologies are categorized into the following four aspects:

1. Technological centrality. Key core technologies occupy a central position within the technological system, driving technological progress and innovation across the entire system [6]. They control the technological high ground within the industrial chain and play a decisive role in both the technology chain and industrial chain [7], providing essential support and foundations for other technologies while leading technological advancement.
2. High technological value. These technologies represent the innovation and application of interdisciplinary, complex knowledge, embodying highly concentrated technical expertise [8]. Their innovations possess high technical sophistication and practical utility, often triggering a cascade of related technological advancements and progress.
3. High economic value. The R&D of key core technologies significantly enhances product performance, promotes new product development, and drives economic growth, serving as the cornerstone for achieving industrial innovation and securing economic benefits [9].
4. Competitive Monopoly. Key core technologies are irreplaceable and difficult to master, forming the foundation for maintaining corporate market competitiveness [10].

Nations or enterprises that control industrial key core technologies can achieve monopolistic positions in international markets [11]. Their knowledge exclusivity provides technological barriers [7], enabling monopolization of products or services under legal protection.

The above four characteristics provide a comprehensive description of the intrinsic attributes, value conversion, and competitive performance of key core technologies. Technological centrality and technological value focus on the core attributes of the technology itself; economic value centers on the technology's value conversion capability, serving as the critical link for translating technological essence into market value and reflecting the industrial empowerment capacity of core technologies. Competitive monopoly power highlights the market competitiveness of the technology, representing the market outcome after the value conversion of core technologies and the key feature distinguishing them from general technologies. These four characteristics encompass the widely recognized attributes of core technologies in existing research, providing a complete definition of the conceptual essence of key core technologies in the intelligent vehicle domain.

The core connotations of these four characteristics and their corresponding mapping relationships to relevant research are shown in Table 1.

Table 1. Mapping of key core technology characteristics and existing studies.

Key Core Technology Characteristics	Core Connotation	Relevant Literature
Technological Centrality	The technology occupies a core/hub position in the technological system, acts as a bridge, dominates the development of the technology chain and industrial chain, and provides fundamental support for other technologies.	Wang & Huang (2023), Yao et al. (2024), Di Stefano et al. (2012), Vázquez Rojo & Visintin (2024) [6,7,12,13]
Technological Value	The technology embodies interdisciplinary and complex knowledge, features high innovativeness and technological advancement, and can drive chain breakthroughs and development of follow-up related technologies.	Lai & Nie (2024), Choi et al. (2021), Yang & Wang (2024) [8,14,15]
Economic Value	The R&D and application of the technology can significantly improve product performance and promote new product development, with strong market potential and profitability, serving as the foundation for industrial innovation and economic benefits.	Kafouros et al. (2021), Di Stefano et al. (2012), Choi et al. (2021) [9,12,14]
Competitive Monopoly	The technology is irreplaceable and difficult to replicate, can form technological barriers, and bring competitive advantages and monopolistic position to the entity.	Wang & Huang (2023), Yao et al. (2024), Feng et al. (2020), Miao et al. (2025), Chih-Yi & Bou-Wen (2021) [6,7,10,11,16]

2.2. Research on the Identification of Key Core Technologies

Patents serve as a vital data source for identifying key core technologies, characterized by their comprehensive, detailed, and standardized disclosure [17]. Traditional identification methods primarily rely on expert experience, whereas patent-based approaches utilize single metrics such as patent citation frequency [4], number of patent families [18], and number of patent claims [19] to identify key core technologies. While simple to implement, this method may overlook other critical dimensions. In contrast, the indicator system method constructs a multidimensional metric framework with weighted indicators to identify key core technologies, offering greater objectivity and comprehensiveness [8].

Additionally, social network analysis constructs co-occurrence networks or patent citation networks based on IPC (International Patent Classification) codes representing specific technological domains. By leveraging characteristics such as centrality and clustering of network nodes, it identifies key nodes within the technology network, thereby determining core technical domains. For instance, Feng et al. [20], Lai et al. [21], and Malhotra et al. [22] constructed patent citation networks to track technological development trajectories and identify core technologies. Hua et al. [23] identified key technologies through node centrality features in IPC co-occurrence networks. While this approach effectively reveals complex structural characteristics among technologies, it may overlook important attributes outside the network. Therefore, this paper integrates IPC co-occurrence networks with a multidimensional indicator system based on both network characteristics and technological importance, addressing the limitations of single-method approaches to enhance the accuracy and comprehensiveness of identifying key core technologies.

In recent years, machine learning and deep learning methods have emerged as a new research focus in patent analysis due to their powerful quantitative analysis and feature extraction capabilities, finding widespread application in patent research within technology-intensive industries. For identifying key core technologies, common machine learning approaches include LDA topic modeling, random forests, and XGBoost. Deep learning methods such as convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and graph neural networks (GNNs) have further expanded the boundaries of patent analysis. The advantages of these emerging methods lie in their higher efficiency in processing massive patent datasets and deeper feature extraction, enabling effective capture of implicit technological associations. However, they also present significant limitations: First, poor model interpretability—deep learning models are often termed “black-box models,” making it difficult to clearly articulate the underlying logic of why a technology is deemed “critical and core,” resulting in low integration with theoretical patent analysis research. Second, high modeling costs arise from the need to fuse features across multiple data sources, including patent text, metrics, and networks. For research focused on identifying key core technologies through matching technical features and core concepts, this approach suffers from methodological redundancy.

Therefore, this study addresses the strengths and limitations of existing methods by integrating IPC co-occurrence network analysis with a multidimensional indicator system. It leverages the high technological convergence and complex network structure of the intelligent vehicle industry, while incorporating entropy weighting and gray relational analysis to quantify technological core value. This integrated approach leverages social network analysis to uncover technological structural connections while employing a multidimensional indicator system to cover core attributes such as technological value, economic impact, and competitiveness, thereby overcoming the limitations of single-method approaches. This methodology prioritizes theoretical interpretability and empirical adaptability. It constructs an indicator system based on the four key characteristics of core technologies, ensuring alignment between identification logic and theoretical foundations. Objective weighting and correlation analysis enable quantitative evaluation, mitigating the subjectivity of expert judgment and the “black box” issues inherent in machine learning models. This approach aligns more effectively with the research objectives and provides a methodologically sound, practical reference for identifying core technologies in technology-intensive industries like intelligent vehicles.

2.3. Analysis of Technological Competitive Dynamics

Analysis of the competitive landscape for key core technologies involves a systematic assessment of the technological R&D capabilities, strategic positioning, development

trends, and competitive relationships among entities within a given technology domain. Its core objective is to identify innovation leaders, potential competitors, and collaborative partners within the field, grasp technological development trends, clarify the primary sources of technological innovation and key target markets, thereby providing decision-making references for industrial innovation planning. For technology-intensive industries such as intelligent vehicles, academia has developed multiple mature frameworks for competitive landscape analysis, which form the critical theoretical foundation of this study.

The core competitive logic of technology-intensive industries revolves around the sequence of “technological innovation capability—patent portfolio—market competition.” Existing mainstream frameworks for analyzing competitive landscapes primarily encompass three categories: First, the technological competitiveness evaluation framework, which centers on patent metrics. By quantifying indicators such as patent application volume, grant volume, citation frequency, and patent family count [24,25], this framework provides a foundational basis for assessing an entity’s technological competitiveness in industrial competition analysis. Second, the core technology portfolio analysis framework focuses on granular dimensions within technological domains. Using methods such as IPC [26] and technology theme clustering, it analyzes entities’ strategic priorities, areas of strength, and technological gaps in core technology fields, revealing the heterogeneity of competitive landscapes. Third, the innovation ecosystem competition framework transcends the limitations of single-entity analysis. It examines the collaborative competitive relationships among enterprises, universities, research institutions, and other entities from the perspectives of industrial chains and innovation chains.

In terms of specific research methodologies and analytical perspectives, existing studies on the competitive landscape of technology-intensive industries have established a multidimensional, multi-tiered research framework. From an analytical viewpoint, this framework primarily encompasses two core levels: the national/regional level and the corporate level. At the national level, the focus is on the global distribution of technological innovation, the technological strengths of various countries, and industrial division of labor. At the corporate level, the emphasis is on the R&D strategies, patent portfolios, and competitive capabilities of leading enterprises. Beyond basic patent quantity statistics and share analysis, quantitative methodologies incorporate techniques such as technological similarity analysis, H-index evaluation, and patent network analysis [27,28]. Technical similarity serves as a core tool for quantifying the convergence of technological layouts between two competitors (countries/enterprises). Through matrix analysis, it identifies which pairs exhibit the most similar layouts and intense homogeneous competition, and which pairs show significant divergence and engage in differentiated competition. The H-index is commonly used to measure technological competitiveness but faces limitations such as age bias, variations in citation practices across patent offices, and technological field heterogeneity. This study restricts its comparative scope to a horizontal comparison within the single technological domain of intelligent vehicles. By employing a unified patent data source and consistent time span, it effectively mitigates the aforementioned biases, ensuring the comparability of the H-index.

As a quintessential technology-intensive industry, intelligent vehicles serve as a core vehicle for low-carbon transportation and sustainable transformation. Their competitive landscape is highly intertwined with sustainable development, characterized by high barriers to technological R&D, global patent positioning, and diverse competitive entities. The refinement of technological innovation systems, alongside the global diffusion and industrial deployment of low-carbon intelligent technologies, directly drives emission reductions, efficiency gains, and the widespread adoption of green mobility in transportation. Consequently, there is an urgent need to integrate and adapt existing analytical

frameworks and methodologies to the industry's specific attributes, enabling precise assessments of its technological competitive landscape.

2.4. Research Review

A comprehensive review of existing studies on the defining characteristics, identification methods, and competitive landscape analysis of key core technologies, as outlined in Sections 2.1–2.3, reveals that the academic community has established a certain theoretical foundation and research methodology in this field. However, further research remains necessary: First, the definition of key core technology characteristics and the corresponding indicator systems lack industrial applicability, and some studies have failed to effectively bridge abstract characteristics with observable patent metrics. Second, identification methods remain relatively limited, with few studies integrating the strengths of different approaches, making it difficult to comprehensively identify both the structural characteristics of technology networks and the multidimensional value of technologies. Third, there is a scarcity of studies that analyze competitive landscapes at the national and corporate levels in conjunction with corresponding key core technologies.

To address these issues, this study constructs a comprehensive identification indicator system tailored to key core technology characteristics. It focuses on the network centrality attributes and significant value attributes of technologies, integrating network analysis, entropy weighting, and gray correlation analysis to achieve objective identification. Simultaneously, it employs a multi-level competitive landscape analysis framework to characterize competitive differences in key core technologies from both national and corporate dimensions, providing a basis for technology strategy formulation. The following sections will detail the specific design and implementation steps of this research.

3. Research Design

This paper constructs an indicator system for identifying key core technologies based on an in-depth analysis of their definitions and characteristics, thereby identifying the key core technologies of the intelligent vehicle industry. It further analyzes the competitive landscape of key core technologies from the perspectives of competing nations and enterprises. The research framework is illustrated in Figure 1.

3.1. Construction of Key Core Technology Identification Indicators

This paper constructs an indicator system based on the conceptual framework and key characteristics of core technologies outlined in the preceding section. It employs technological network connectivity and technological significance as primary indicators for identifying core technologies within the intelligent vehicle industry. The secondary indicators under technological network connectivity are technological centrality and technological position. The secondary indicators under technological significance include technological value, economic value, and competitive monopoly. To ensure the scientific rigor and validity of the identification framework, this study constructs hierarchical indicators based on two principles: high alignment with the four core characteristics of key core technologies (technological centrality, technological value, economic value, and competitive monopoly) and robust support from patent metrics theory and empirical research. The specific selection criteria for each tertiary indicator are outlined below, with all indicator levels and definitions summarized in Table 2:

1. Technological Centrality. This dimension captures a technology's central role within an industry, measured by two complementary indicators:
 - (1) Degree Centrality: Reflects the frequency of connections between a technology and others in a co-occurrence network, measuring its importance within the

network. In patent co-occurrence networks, higher degree centrality indicates that a technology frequently co-appears with others in patents, signifying a more pivotal position within the field [29]. This serves as the foundation supporting the development of multiple related technologies, aligning with the “core supporting role” characteristic of key core technologies.

- (2) **Betweenness Centrality:** Measures the frequency of a technology node appearing on the shortest paths between all other nodes in the network. Higher betweenness centrality indicates that the technology serves as a crucial “bridge” for knowledge flow and technology diffusion, controlling connection channels between different technological domains. This corresponds to the “decisive role” of key core technologies within the technology chain.
2. **Technological Value.** This dimension quantifies technological advancement and innovative contributions, with indicators selected to balance long-term impact and technological comprehensiveness.
 - (1) **Citation Count:** A high number of citations typically indicates significant technological value within the relevant field [30]. Cumulative citations reflect sustained recognition from both academia and industry, aligning with the “foundational and enduring influence” characteristic of key core technologies. Patents with high citation counts often incorporate original, foundational technical elements, achieving breakthroughs prior to subsequent inventions. They serve as crucial references for future technological development and significantly shape the trajectory of technological advancement.
 - (2) **Technological Coverage:** This refers to the number of distinct technical fields addressed by the patent. Broader coverage indicates integration of cross-disciplinary knowledge, reflecting greater technical complexity and comprehensiveness. Research demonstrates that extensive technological coverage enhances the perceived value of patented technologies [8], aligning with the “high technological value” characteristic of key core technologies.
 3. **Economic Value.** This dimension focuses on a technology’s market potential and profitability, selecting indicators suited to the global competitive landscape of the intelligent vehicle industry.
 - (1) **Patent Cooperation Treaty (PCT) Application Volume:** Filing PCT patents requires substantial financial and human resources, prompting applicants to seek international protection only when anticipating high returns. PCT international applications reflect the technological significance of the patented invention and the applicant’s intent to capture international markets. This metric partially measures patent quality, as multinational protection enables enterprises to gain greater economic benefits from global market expansion, demonstrating the technology’s high economic value. The PCT application volume for a specific IPC technology node is calculated as the average of all PCT applications under that IPC. This metric reflects the overall international market deployment potential of that technology node.
 - (2) **Technological Application Scope:** Measured by the number of national economic classifications covered by the patented technology. A broader application scope indicates the technology can be deployed across multiple products, industries, or markets, yielding higher potential economic returns. For the smart automotive industry—which integrates automobile manufacturing, information technology, and transportation services—this metric effectively captures the cross-industry economic value of core technologies.

4. **Competitive Monopoly.** This dimension characterizes the exclusivity and irreplaceability of technology, with indicators covering both technical and market dimensions.
 - (1) **Number of Claims:** Patent claims are legal documents defining the scope of technical protection. A higher number of claims indicates more comprehensive coverage and greater detail in technical protection. This directly increases competitors' "cost of circumvention," thereby forming a technological monopoly barrier. Additionally, to mitigate statistical bias from variations in published texts and translations across patent offices, all claim data in this study is sourced from standardized patent publications with consistent statistical criteria. For the rare instances where claim counts were missing, the mean claim count of patents within the same IPC was used as a fill-in value. This approach prevents sample loss while ensuring data integrity and statistical validity.
 - (2) **Number of Patent Families:** The number of patent families represents the quantity of protections granted for the same patent technology across different countries. A higher number indicates broader global market coverage, preventing competitors from deploying similar technological products in multiple key markets and thereby establishing market-level monopoly barriers. The number of claims and the number of patent families collectively capture the dual dimensions of "technological exclusivity" and "market exclusivity" in competition monopoly assessments.

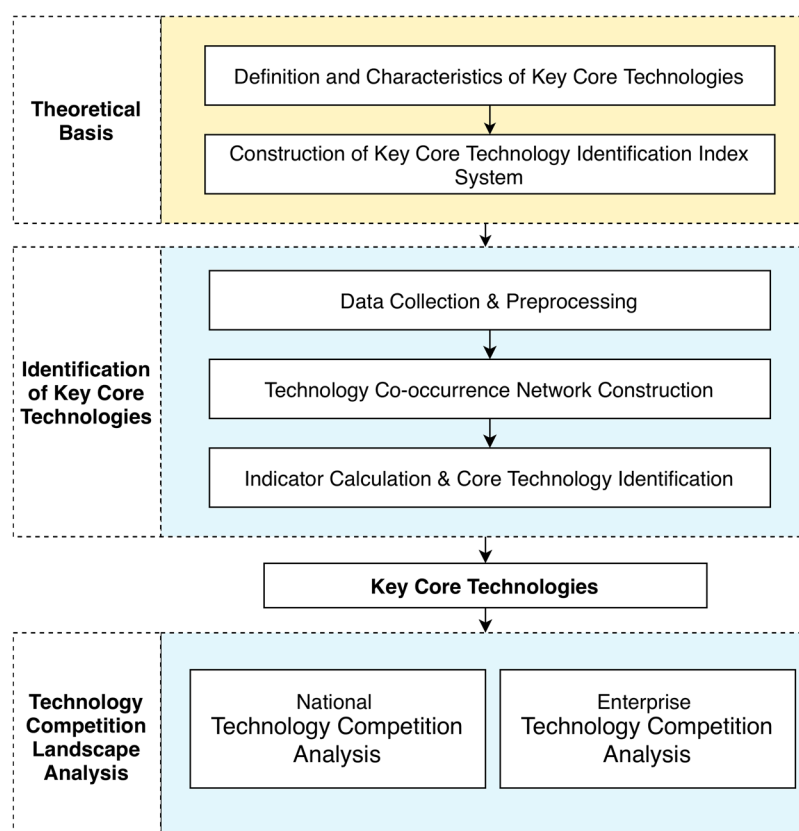


Figure 1. Research Framework. Notes: The section with a yellow background represents theoretical analysis, while the section with a blue background represents empirical research.

Table 2. Key Core Technology Identification Index System.

Primary Indicators	Secondary Indicators	Tertiary Indicators	Indicator Definition
Technical Network Features	Technological Centrality	Degree Centrality	The frequency of edges connecting a given technology to other technologies within a co-occurrence network, measuring the technology's importance within the network [29].
		Betweenness Centrality	The frequency with which a technology node appears in all shortest paths within the network, measuring the technology's importance within the network [31].
Technical Value Attributes	Technological Value	Citation count	The higher the frequency of subsequent patent citations, the greater the influence of the technology on subsequent developments, indicating stronger importance and higher technological value [30].
		Technical Coverage	The greater the number of different technical fields covered by a patent, the broader its technical scope and the higher its technological value [8].
	Economic Value	Patent Cooperation Treaty (PCT) Application Volume	A higher number of PCT applications indicates broader international market potential for the technology, thereby increasing its economic value [24].
		Technological Application Scope	A greater number of national economic classifications indicates broader industry applicability and wider application scope, thereby increasing economic value [32].
	Competitive Monopoly	Number of Claims	A higher number of claims indicates broader protection scope and stronger competitiveness [6].
		Number of Patent Families	The number of protections a single patent receives across different countries. A larger number of patent families indicates greater international influence and stronger competitiveness for the technology [33].

3.2. Methods for Identifying Key Core Technologies

3.2.1. Construction of Technology Co-Occurrence Networks

The patent technology co-occurrence network analysis method reflects the correlation between technologies based on the co-occurrence of different technical categories in the same patent. The internationally accepted International Patent Classification (IPC) codes cover almost all technical fields. Constructing a technology co-occurrence network through IPC codes enables the identification of technologically important nodes in the network, providing crucial support for recognizing key technologies. The IPC system divides technical fields into 8 sections, each further subdivided into classes, subclasses, main groups, and subgroups. Considering the complexity of the industrial technology system, the main group level of IPC codes is selected for analyzing the relevant attributes and co-occurrence relationships of technical fields [34].

After acquiring and processing patent data, IPC codes are extracted to construct a technology co-occurrence matrix, which is then used to build a technology co-occurrence network. In this network, nodes represent different IPC codes, edges denote the co-

occurrence relationship between two distinct IPC codes in a single patent, and edge weights correspond to the frequency of co-occurrence of the two IPC codes.

3.2.2. Technology Set Screening Method

Price's Law, proposed by Derek de Solla Price in the 1960s, describes the unequal distribution of contributions and outputs within the scientific community. Its core principle states that half of the contributions in a field originate from a group of its most prolific authors. This methodology has since been applied to technology identification research. In this study, all technologies within the intelligent vehicle industry constitute a technological collective. Key core technologies are essentially a "superior technology subset" within this collective—technologies that, after undergoing market and technological iteration, possess high adaptability, significant influence, and the ability to sustainably transmit technological advantages. To more accurately identify key core technologies, after collecting patent data to obtain the set of IPC technology categories for identification, the Price formula is used to scientifically set thresholds. This enables preliminary screening of the technology set occupying a significant position, which serves as the foundation for subsequent key core technology identification. The Price formula is: $M = 0.749\sqrt{N_{max}}$, where M is the threshold and N_{max} is the maximum value of the indicator. Technologies with indicator values $\geq M$, selected via the Price formula, form the foundational set for identifying key core technologies within the domain.

3.2.3. Indicator Weighting and Key Core Degree Measurement Method

The entropy weight method is an objective weighting approach that determines weights based on the dispersion of indicator data. It objectively reflects the importance and information content of each indicator within the evaluation system, avoiding the subjective weighting bias inherent in simple weighted scoring. This method is widely applied in multi-indicator comprehensive evaluations [6]. Grey Relational Analysis (GRA) judges correlation based on consistency in trend changes, analyzing the degree of association between objects under comparison and reference objects. This paper combines the Entropy Weighting Method and GRA to score each technology domain, calculating the key core value of the technology to make the evaluation results more evidence-based, objective, and accurate. Compared to alternative approaches like TOPSIS, VIKOR, or simple weighted scoring, this combined method demonstrates superior adaptability within the research context. Firstly, the core objective of this study is to identify key core technologies that simultaneously possess technological network status, technological value, economic value, and competitive monopoly characteristics. The Entropy Weighting Method captures the variability in indicator dispersion across the critical attribute dimensions of this study, ensuring the objectivity and rationality of weight allocation. Meanwhile, GRA focuses on the correlation between indicators and ideal core technologies, addressing the Entropy Weighting Method's limitation of solely addressing weight distribution without directly assessing core significance. Their combination achieves the dual objectives of objective weighting and quantifying core significance. Second, the patent data in this study exhibits strong sample heterogeneity and non-normal distribution in some indicators. GRA imposes no strict requirements on sample size or data distribution, eliminating the need to assume normal distribution. This avoids issues of distorted evaluation results caused by data heterogeneity in the patent data context of this study.

3.3. Framework for Analyzing Technological Competitive Dynamics

To deeply analyze the competitive landscape of key core technologies in the intelligent vehicle sector, this study identifies critical technologies and analyzes competing entities at both national and corporate levels using patent-related metrics and temporal

trends. Descriptive statistics form the foundation for presenting fundamental characteristics of the competitive structure. Additionally, a technology similarity matrix and the H-index are introduced to quantify competitive relationships among nations and enterprises.

1. **National Level.** The country of origin of technology reflects the national distribution of patent applicants, which is usually determined based on the country information in the priority number. The number of patent applications serves as a crucial indicator to measure a country's technological innovation capability and activity [35]. This paper analyzes the distribution of key core technology source countries at the national level, the distribution and technological similarity of key core technologies among major competing nations, and the proportion of key core technologies. This approach identifies technologically leading countries, assesses global technology diffusion trends, and evaluates national technological competitiveness. Among these, technological similarity is commonly measured using cosine similarity [27]. Compared to methods such as Euclidean distance and Pearson correlation coefficient, this approach solely compares the structure and proportion of technological portfolios, unaffected by the total volume of national patents. It accurately reflects the similarity in strategic positioning across countries regarding key core technologies. Therefore, this study employs cosine similarity to construct a technological similarity matrix.

The calculation formula is: $S_{ij} = \frac{\sum_{k=1}^{15} (Z_{ik} \times Z_{jk})}{\sqrt{\sum_{k=1}^{15} Z_{ik}^2} \times \sqrt{\sum_{k=1}^{15} Z_{jk}^2}}$, where S_{ij} represents the similarity

coefficient between country i and country j . A value closer to 1 indicates more pronounced homogeneous competition between the two countries, while a value closer to -1 indicates more pronounced heterogeneous competition. Z_{ik} and Z_{jk} represent the standardized indicator values for the k th key core technology between the two countries. The numerator of the formula reflects the degree of overlap in the technological layouts of the two countries across n core technologies, while the denominator eliminates differences in the total patent volumes of the countries through vector normalization, ensuring the results focus solely on the structural similarity of technological layouts.

2. **Corporate Level.** Patent assignees hold exclusive rights, licensing rights, and transfer rights of patents, among others. The number of their patent applications reflects an enterprise's technological R&D and innovation capabilities, as well as its market competitive advantages. At the enterprise level, this study analyzes the distribution of major patent assignees, the quantity trend of key core technologies, and their competitive strength, so as to identify technologically leading enterprises and assess their competitive power and technological development trends. Enterprise competitive strength is measured by the H-index [36]. By definition, if an assignee has N patent documents each cited at least N times, their H-index is N . A higher H-index indicates greater influence of the patent technology.

4. Empirical Analysis

4.1. Sample Selection and Data Sources

This paper focuses on the intelligent vehicle industry to identify its key core technologies. Patent data is sourced from the incoPat patent database, which contains over 170 million foundational patent records from 176 countries, organizations, and regions worldwide. The database undergoes dynamic updates at least three times weekly to ensure users access the latest patent information. It features specialized collection and processing of patent data from over 30 major countries, offering comprehensive data fields and high data accessibility.

This paper employs a combined search method using “keywords” and “IPC codes.” Based on the definition and connotation of intelligent vehicles, and in conjunction with relevant literature [37], the following Chinese and English synonymous search keywords were identified: intelligent vehicles, autonomous driving, intelligent connectivity, etc. The search keywords were simultaneously restricted to the vehicle category, excluding non-vehicle-related keywords such as aircraft, vessels, and submersibles. Considering that technology evolves iteratively, early patents represent the “prototypes and foundations” of key core technologies. Our search revealed that patents related to intelligent vehicle technology existed as early as 1950. To comprehensively trace the development trajectory of core intelligent vehicle technologies, the search timeframe spans from 1950 to 2024. Invention patents are generally considered to possess higher technical content and are more frequently used in studying technological innovation. Therefore, the patent type searched is granted invention patents. After repeated attempts and comparisons, the final search formula was determined as:

((((TIAB = (“intelligent vehicle” OR “intelligent car” OR “smart vehicle” OR “smart car” OR “autonomous vehicle” OR “autonomous car” OR “automated vehicle” OR “self-driving car” OR “driverless vehicle” OR “driverless car” OR “unmanned car” OR “intelligent connected vehicle” OR “autonomous driving” OR “automatic driving” OR “connected car” OR “connected vehicle”) AND TIAB = (car OR vehicle OR automobile) NOT TIAB = (“aerial vehicle” OR “air vehicle” OR “underwater vehicle” OR “flight vehicle” OR airplane OR aircraft OR aeronautical OR aerobot OR aerocraft OR “flying machine” OR bicycle)) AND (IPC = (B OR G OR H))) AND (AD = [19500101 TO 20241231])) AND (PAT = (“4”)).

The search was conducted on 1 April 2025, with a time span of 1950–2024, yielding a total of 47,468 authorized invention patents. After manual inspection, invalid data, duplicate entries, and data unrelated to intelligent vehicle industry technology were removed by eliminating fields missing titles, abstracts, or IPC numbers. The criteria for excluding various types of data are as follows: Invalid data is determined by the absence of at least one of the title, abstract, or IPC number. Duplicate data is identified by non-unique patent publication numbers, with patents having identical publication numbers removed. Irrelevant data is excluded when neither the patent title, abstract, nor claims contain keywords from the intelligent vehicle domain specified in the search query, such as patents originating from the insurance or financial sectors, thereby avoiding subjective judgment bias. The final dataset comprises 46,373 patents.

4.2. Metric Measurement and Weighting

A Python (version 3.8.3) program was developed to extract the main group codes of patent IPC and generate a technology co-occurrence matrix. The primary IPC code reflects the core technical characteristics of a patent and is a key indicator of technological innovation [38,39].

Focusing on the primary IPC code avoids ambiguity and duplicate counting issues caused by multiple secondary IPC codes, ensuring the accuracy of technical node identification within co-occurrence networks. Therefore, 842 distinct primary IPC codes identified in patents related to the intelligent vehicle field were selected for further research on key core technology identification.

Based on the co-occurrence matrix of technologies, social network analysis (SNA) methods were employed to calculate the centrality of each technology node using UCINET (version 6), thereby obtaining the network connectivity metrics for the technology network. Preliminary core screening and refinement of technology codes were performed using the Price formula mentioned in Section 3.2.2. Marginal codes with low technological relevance were eliminated. A threshold for centrality metrics was calculated, selecting 202

technology classification codes with both degree and centrality metrics $\geq M = 0.749 * \sqrt{N_{max}}$ (where N_{max} represents the maximum value of the metric) as the foundational set for identifying key core technologies within this domain.

A Python program was developed to traverse key attribute fields within patent data, calculate metric values for each technical classification, and generate a technical core criticality judgment matrix. Due to significant differences in the dimensions and magnitude scales of various evaluation metrics, this study performed range normalization on all metric data in the initial judgment matrix prior to calculating weights using the entropy weight method. This approach eliminates dimensional effects and mitigates scale sensitivity interference in the analysis results. The range normalization formula is: $X'_{ij} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)}$, where X_{ij} is the raw value of the j indicator for the i technical category, $\min(X_j)$ and $\max(X_j)$ are the minimum and maximum values of the j indicator, respectively, and X'_{ij} is the normalized standard value. After normalization, all indicator values are mapped to the interval [0, 1]. The standardized judgment matrix is shown in Table 3.

Table 3. Standardized Judgment Matrix for Key Core Degrees (Partial).

IPC	Citation Count	Technical Coverage	PCT Application Volume	Technological Application Scope	Number of Claims	Number of Patent Families	Degree Centrality	Betweenness Centrality
G05D1	0.113	0.083	0.268	0.059	0.594	0.198	1.000	1.000
B60W30	0.040	0.058	0.373	0.032	0.456	0.217	0.992	0.234
G08G1	0.064	0.083	0.406	0.052	0.434	0.237	0.940	0.278
B60W50	0.026	0.054	0.349	0.037	0.481	0.201	0.763	0.116
B60W40	0.020	0.053	0.322	0.036	0.459	0.193	0.651	0.120
G01C21	0.090	0.109	0.374	0.070	0.564	0.258	0.516	0.099
B60W60	0.003	0.041	0.280	0.038	0.514	0.161	0.502	0.119
B60W10	0.026	0.073	0.315	0.039	0.447	0.219	0.322	0.083
H04W4	0.028	0.081	0.361	0.183	0.632	0.186	0.300	0.103
G06V20	0.004	0.100	0.229	0.086	0.572	0.121	0.275	0.034

Subsequently, the entropy weight method was applied to calculate the information entropy and entropy weights for all identification indicators. The resulting weights for each indicator are presented in Table 4. The weight distribution reveals that degree centrality (0.318) and intermediary centrality (0.278) under the technological network characteristics dimension significantly exceed the weights of all indicators under the technological value attributes dimension. Theoretically, the core characteristic of key core technologies is technological centrality. As the pivotal nodes within the technological system, they play a decisive role in the connectivity and transmissibility of the entire technological network, making them the primary dimension for identifying key core technologies. From a data perspective, the greater the weight, the higher the objective weight assigned to the network centrality indicators in this study. This is because these indicators demonstrate significantly superior discrimination capabilities across different technology classifications compared to other indicators.

Table 4. Weights of Key Core Degree Evaluation Indicators.

Primary Indicator	Secondary Indicators	Third-Level Indicator	Indicator Weight
Technical Network Features	Technological Centrality	Degree Centrality	0.318
		Betweenness Centrality	0.278
Technical Value Attributes	Technological value	Citation Count	0.160
		Technical Coverage	0.051
	Economic Value	PCT Application Volume	0.050
		Technology Application Scope	0.065

Competitive Monopoly	Number of Claims	0.020
	Number of Patent Families	0.058

4.3. Key Core Technology Identification Results

Based on the indicator values for each technology classification, the correlation coefficients and indicator weights were obtained using grey relational analysis, and the key core degree values of each technology were calculated accordingly. Table 5 presents the top 15 IPC technical classification codes ranked by scores, their corresponding technical meanings, and key core degrees.

Table 5. Classification Codes and Technical Meanings of Key Core Technologies.

Rank	IPC	Technical Meaning	Key Core Degree
1	G05D1	Control or regulation systems for non-electrical variables, particularly for the position, course, altitude, or attitude of vehicles, e.g., autopilots	0.748
2	B60W30	Use of Road Vehicle Driving Control Systems	0.572
3	G08G1	Traffic Control System for Road Vehicles	0.549
4	B60W50	Components for Road Vehicle Driving Control Systems	0.464
5	G06F15	Digital data processing, involving general-purpose digital computers; general-purpose data processing equipment	0.461
6	B60W40	Determination or calculation of driving parameters for road vehicle driving control systems	0.435
7	H05B6	Light sources or lighting systems heated by electric, magnetic, or electromagnetic fields	0.427
8	G01S5	Systems for positioning or navigation using radio waves	0.418
9	G06F19	Digital data processing involving specific digital computational models or methods, such as artificial intelligence, machine learning, or data processing algorithms	0.417
10	G01C21	Navigation; navigational instruments	0.415
11	B60W60	Particularly suitable for drive control systems of autonomous road vehicles	0.405
12	H04L5	Digital information transmission, involving devices providing multi-purpose functionality for transmission channels	0.391
13	H04W72	Wireless communication networks, relating to local resource management	0.388
14	H04L27	Digital data processing, involving methods or apparatus for processing data by means of instructions or content of the data to be processed	0.388
15	G06F7	Services specifically for wireless communication networks; facilities	0.385

To validate the reliability of the research findings, a sensitivity analysis was conducted by adjusting the weights. Five weight adjustment schemes were established, modifying the weights of centrality and mediating centrality (simultaneously decreasing or increasing them by 20% or 40%, while maintaining the fixed ratio between the two weights). The core values and rankings for each technology category were recalculated under each scheme, and the overlap of the top 15 core technologies across different schemes was compared. Results showed that under all five schemes, the overlap rate of the top 15 core technologies reached 93–100%, with no significant changes in their core-ness rankings (G05D1, B60W30, and G08G1 consistently ranked in the top three). This indicates that the dominant weighting of network centrality metrics in this study did not introduce bias into core technology identification results, demonstrating robust and reliable research conclusions.

The results indicate that key core technologies in the intelligent vehicle sector include G05D1 (control of vehicle position, course, altitude, or attitude), B60W30 (use of road vehicle driving control systems), G08G1 (traffic control systems for road vehicles), B60W50

(components of road vehicle driving control systems), G06F15 (General-purpose digital computers; general-purpose data processing apparatus), B60W40 (Determination or calculation of driving parameters for road vehicle driving control systems), H05B6 (Light sources or illumination systems heated by electric, magnetic, or electromagnetic fields), G01S5 (Systems for positioning or navigation using radio waves), G06F19 (Specific digital computing or data processing algorithms), G01C21 (Navigation, navigational instruments), B60W60 (Drive control systems especially for autonomous road vehicles), H04L5 (Devices providing multiple uses for transmission channels), H04W72 (Local resource management), H04L27 (Methods or apparatus for data processing by performing operations on instructions or contents of data to be processed), G06F7 (Services, facilities specifically for wireless communication networks).

Based on the functional architecture of intelligent vehicle technology [40] and integrating the core technological chain of “perception-decision-execution-coordination” [41], these 15 key core technologies are categorized into four domains: autonomous driving and vehicle control, intelligent transportation and vehicle–road coordination, onboard computing and data processing, and powertrain system integration and optimization. Among these, the autonomous driving and vehicle control domain (e.g., G05D1, B60W30, B60W50, B60W40, B60W60) focuses on the “decision-execution” process for autonomous vehicle operation. It concentrates on core technologies such as vehicle posture control, driving parameter calculation, and autonomous drive control. These correspond to technologies directly related to vehicle driving control within the IPC. Collectively, they form the core control unit for intelligent vehicle autonomous operation, representing key technologies at the “execution layer.” The core function of the intelligent transportation and vehicle–road coordination domain (e.g., G08G1, G01C21, G01S5) is to enable collaborative interaction between vehicles and external environments (traffic systems, road infrastructure). It focuses on technologies such as traffic control, vehicle–road communication, and navigation positioning, corresponding to the “perception-coordination layer” technologies of intelligent vehicles. This addresses information exchange and collaborative decision-making between vehicles and their environment. The core function of the in-vehicle computing and data processing domain (e.g., G06F15, G06F19, H04L5, H04W72, H04L27, G06F7) is to provide “computational-data support” for intelligent driving. It focuses on technologies such as digital data processing, artificial intelligence algorithms, and wireless communication, corresponding to the “decision-making layer” technology of intelligent vehicles. This domain serves as the core computational power support for processing perception data and enabling intelligent decision-making. The core function of the powertrain system integration and optimization domain (e.g., H05B6) is to achieve the adaptive integration of “powertrain-intelligence technologies.” It focuses on the integrated optimization of vehicle powertrain systems and intelligent control technologies, corresponding to the “execution-adaptation layer” technologies of intelligent vehicles. This addresses power supply and energy consumption optimization challenges in intelligent driving scenarios. These technologies are interconnected and synergistic, collectively forming the core framework of the intelligent vehicle technology system and driving its advancement toward high levels of intelligence, automation, and connectivity.

4.4. Competitive Landscape Analysis of Key Core Technologies for Intelligent Vehicles

Based on the identified key core technologies in the intelligent vehicle domain, patents were selected where the primary IPC codes encompass the top 15 key core technologies by criticality ranking [42]. Since the primary IPC codes represent the core technical attributes of each patent, screening sample patents based on this standard ensures that subsequent competitive landscape analysis remains focused on the core technological domains of intelligent vehicles. Further analysis of their technological competitive landscape

was conducted to gain deeper insights into the development dynamics and competitive structure of this technological field. Additionally, the priority country serves as the mainstream standard for defining the origin of technology in the patent field. It is widely adopted by international organizations such as the OECD and the World Intellectual Property Organization (WIPO), ensuring strong comparability and international applicability. The priority country is typically highly correlated with the location of a patent's first disclosure of R&D, thereby reflecting the original attribution of technological development to a certain extent. It should be clarified that the priority country classification cannot distinguish between different transnational application patterns—such as domestic R&D with domestic filing, domestic R&D with overseas filing, or overseas R&D with domestic filing—which may partially affect the alignment between a country's patent portfolio size and its actual R&D capabilities. Subsequent cross-national technological competition analysis in this study will focus on the attribution patterns and strategic deployment characteristics of patented technologies.

4.4.1. Analysis of Technological Competition by Country

1. Distribution of Technology Origin Countries

The distribution of countries holding patents for key core technologies in intelligent vehicles is shown in Figure 2. Based on the number of patent applications filed by each country, the top five nations in terms of patents related to key core technologies are China, the United States, Japan, Republic of Korea, and Germany. These five countries collectively account for 87.22% of global patents for key core technologies. To address the limitations of the single priority country classification method, patents within the same patent family were consolidated into a single entry. The country of origin for patent families was determined based on the parent country of the R&D entity. After this recalculation, the patent landscape and ranking of major competing nations remained fundamentally unchanged: the United States, Japan, and China continue to be the top three holders of core technology patents for intelligent vehicles.

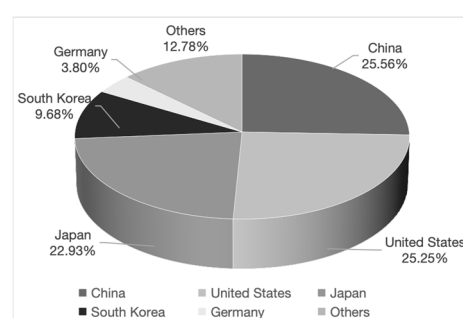


Figure 2. Distribution of Patent Origin Countries for Key Core Technologies.

The high proportion fully reflects the distinctive characteristics of the global intelligent vehicle industry's competitive landscape: First, technological innovation resources exhibit a high degree of concentration. Key core technologies for intelligent vehicles belong to a typical high-investment, high-complexity, and high-barrier domain, requiring long-term accumulation of knowledge in automotive engineering, information technology, and control systems. These five nations—China, the United States, Japan, Republic of Korea, and Germany—possess advantages in industrial foundations (such as traditional automotive manufacturing and electronics industries) and R&D investment, forming a “core-periphery” competitive model. This means technological innovation resources are concentrated in core nations, while most other countries occupy positions as technology followers or adopters. The 87.22% patent share indicates these five nations control the

core segments of the intelligent vehicle technology chain and industrial chain. Their technological positioning and patent barriers will determine the entry thresholds and development paths for other countries in this sector. This pattern also signifies that global competition in the intelligent vehicle industry is no longer fragmented regional rivalry but an intense contest among core nations over key core technologies, standard-setting, and market segmentation.

The remaining 12.78% falls under the “Others” category, primarily comprising countries/regions with dispersed patent portfolios. France (1.2%) and the United Kingdom (0.7%) stand out most prominently, followed by India (0.3%), Russia (0.3%), and over 20 countries/regions with shares below 0.1% (e.g., Italy, Israel, Australia). Most emerging players remain in the early stages of accumulation within this sector. However, their deployments may potentially serve as complementary additions to the global industrial chain in the future.

2. Distribution of Key Core Technologies Among Major Competitor Nations

The distribution rankings of key core technology patents across the five major competing nations are shown in Table 6. It should be noted that patent output across countries is influenced by multiple factors, including the scale of industrial R&D and the intensity of policy support, making direct comparisons of absolute patent counts between nations inherently limited. Examining the patent focus in key technological domains reveals that China, the United States, and Japan hold significant patent portfolios in G08G1, B60W30, and G05D1—indicating strategic technological positioning in vehicle control systems and interactive control systems for traffic environments. The United States centers its patent strategy around G05D1 (automated vehicle control systems), with patents in this field accounting for over 35% of its total core technology patents. Republic of Korea and Germany have developed substantial patent portfolios in the B60W30 technology domain, reflecting their research emphasis on vehicle driving control technologies. Additionally, Republic of Korea focuses on developing wireless communication networks and digital information transmission technologies, as represented by patents in H04W72 and H04L5.

Table 6. Ranking of Key Core Technology Distribution in Major Competing Countries.

Country	China		United States		Japan		Republic of Korea		Germany	
Ranking	IPC	Patent Counts	IPC	Patent Counts	IPC	Patent Counts	IPC	Patent Counts	IPC	Patent Counts
1	G08G1	1359	G05D1	2155	G08G1	1905	B60W30	438	B60W30	203
2	B60W30	1268	B60W30	833	B60W30	1217	G05D1	370	G05D1	199
3	G05D1	1109	G08G1	699	G05D1	783	H04W72	357	B60W50	167
4	B60W60	776	B60W60	620	B60W50	667	B60W60	217	G08G1	121
5	G01C21	641	G01C21	584	G01C21	326	H04L5	215	B60W40	77
6	B60W50	441	B60W50	500	B60W60	236	G08G1	200	G01C21	57
7	B60W40	310	B60W40	247	B60W40	213	B60W50	189	B60W60	47
8	H04W72	52	H04W72	93	G06F15	14	B60W40	142	G06F7	11
9	H04L5	28	H04L5	73	G06F7	14	G01C21	88	G01S5	3
10	G01S5	9	G06F7	49	G06F19	8	H04L27	34	G06F15	3

To further investigate the overall competitive landscape of key core technologies across major competitor nations, we quantified the number of critical core technologies in four domains: autonomous driving and vehicle control, intelligent transportation and vehicle–road coordination, onboard computing and data processing, and powertrain system integration and optimization. After standardizing the data using Z-scores, we calculated the similarity between country vectors using cosine similarity to derive a technology similarity matrix, as shown in Table 7.

Table 7. Technology Similarity Matrix of Major Competing Countries.

	China	United States	Japan	Republic of Korea	Germany
China	1	−0.008	0.311	−0.644	−0.582
United States	−0.008	1	0.261	−0.153	−0.637
Japan	0.311	0.261	1	−0.749	−0.304
Republic of Korea	−0.644	−0.153	−0.749	1	0.366
Germany	−0.582	−0.637	−0.304	0.366	1

The results indicate that China's technological similarity with Republic of Korea (−0.644) and Germany (−0.582) is ≤ -0.5 , reflecting significant differentiation in technological positioning. All countries have increased investments in autonomous driving and vehicle Germany (−0.582) both exhibit a technological similarity ≤ -0.5 , indicating significant differentiation in their technological layouts. All countries have increased deployments in autonomous driving and vehicle control. Republic of Korea focuses more on hardware integration for onboard computing and data processing, while Germany emphasizes powertrain system integration and optimization. This reverse layout suggests that China, Republic of Korea, and Germany face lower market competition conflicts in global key core technology sectors, enabling technological complementarity. China and the United States (−0.008) exhibit near-zero technological similarity, indicating no discernible alignment in technology deployment and extremely low levels of homogeneous competition. China and Japan share a similarity of 0.311, indicating low similarity. Both focus on autonomous driving and vehicle control, as well as intelligent transportation and vehicle–road coordination technologies. The United States and Germany (−0.637) and Japan and Republic of Korea (−0.749) exhibit significant differences in competitive layouts, while Republic of Korea and Germany (0.366) and the United States and Japan (0.261) show relatively similar technological layouts. Overall, the similarity among the five nations in the four key core intelligent vehicle technology directions did not exceed 0.4. Moreover, the fact that similarities between more than half of the countries were ≤ -0.5 indicates that the primary competing nations in global intelligent vehicle core technologies have formed a competitive landscape characterized by “differentiated technological paths and complementary tracks.” There are no obvious homogeneous technological competition clusters, which aligns highly with the characteristics of global division of labor in the intelligent vehicle industry and provides a cooperative foundation for the sustainable development of the global intelligent vehicle industry.

3. Proportion of Key Core Technologies Among Major Competitor Nations

The proportion of key core technologies in the intelligent vehicle sector among major competing nations is illustrated in Figure 3. From 2005 to 2023, the proportion of patents related to key core technologies in the intelligent vehicle field among the five countries showed a fluctuating upward trend. R&D investment and technological competition in this field among various countries have become increasingly intense.

Japan's proportion of R&D investment in key core technologies significantly exceeds that of other nations. As a traditional automotive powerhouse, Japan possesses decades of technological accumulation in core domains such as automotive powertrain systems, vehicle control, and automotive-grade components. Its patent output in key core technologies demonstrates both a substantial base and a dominant share. The United States and Germany exhibit relatively high proportions of key core technology patents, reflecting their patent strategies that balance in-depth research into core technologies with comprehensive coverage of technological systems. China's proportion remains relatively low, indicating substantial room for improvement in R&D for key core technologies. Since 2014, the proportion of key core technologies has gradually stabilized above 40%.

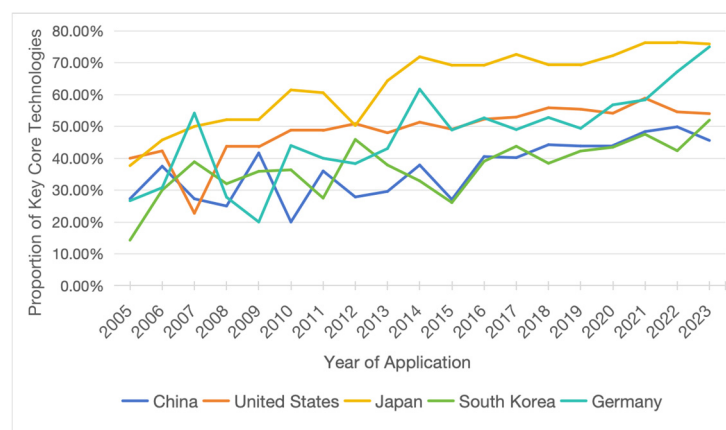


Figure 3. Proportion Trend of Key Core Technologies in Major Competing Countries.

4.4.2. Analysis of Technological Competitors

1. Distribution of Major Patent assignees

Table 8 shows the patent counts and proportions of the top 20 patent assignees by total number of patents for key core technologies in the intelligent vehicle sector. It should be noted that the core technology patent data analyzed in this section represents the total volume of publicly disclosed patent portfolios held by enterprises. This includes patents obtained through independent R&D as well as acquired patents obtained via corporate mergers and acquisitions, patent transfers, licensing, and other means. Due to limitations in patent acquisition data collection methods and disclosure levels, manually sorting and verifying the acquisition method for each individual patent would incur substantial costs and cannot guarantee data completeness or accuracy. Therefore, this section focuses on the overall technological landscape of corporate patent portfolios. The data indicates that the primary competitors in this field are traditional automakers, technology companies, autonomous driving enterprises, and automotive parts suppliers. This multi-stakeholder participation complicates the competitive landscape. These entities focus their R&D efforts on key core technologies such as G05D1, G08G1, B60W30, B60W50, B60W60, G01C21, and B60W40. These technologies emphasize the integration and coordination among internal vehicle systems and interaction with external traffic environments, relying on advanced sensors and communication technologies to achieve vehicle automation and intelligence, thereby enhancing traffic safety, efficiency, and sustainability.

Table 8. Patent Quantity and Proportion of Key Core Technology Patents for Top 20 Patent Assignees.

Rank	Assignee(Country of Origin)	Patent Counts	Proportion	Rank	Assignee(Country of Origin)	Patent Counts	Proportion
1	Toyota Motor Corporation (Japan)	2174	9.3%	11	Volkswagen (Germany)	283	1.2%
2	Baidu (China)	935	4.0%	12	Robert Bosch (Germany)	274	1.2%
3	Samsung Group (Republic of Korea)	911	3.9%	13	Huawei Technologies (China)	260	1.1%
4	Honda Motor (Japan)	734	3.1%	14	Aurora Innovation (United States)	258	1.1%
5	Waymo (United States)	655	2.8%	15	Ford Motors (USA)	220	0.9%
6	Denso Corporation (Japan)	559	2.4%	16	LG Corporation (Republic of Korea)	210	0.9%
7	General Motors (USA)	555	2.4%	17	Apollo Intelligent Technology (China)	185	0.8%

8	Nissan Motor (Japan)	526	2.2%	18	Motional (United States)	174	0.7%
9	Mitsubishi Motors (Japan)	353	1.5%	19	Zoox (United States)	174	0.7%
10	Hyundai Motors (Republic of Korea)	353	1.5%	20	Changan Automobile (China)	144	0.6%

Toyota Motor Corporation, a traditional automaker, ranks first in the number of patents related to key core technologies, demonstrating its deep accumulation in technological R&D and market positioning. This may also include patents acquired through industrial mergers and acquisitions. Technology companies like Baidu and Samsung rank high in overall patent layout, reflecting the breadth of their technological layout and participation in core technologies within the intelligent vehicle supporting technology sector. This represents a comprehensive outcome of both independent R&D and ecosystem collaboration. The strategic positioning of Baidu, Samsung Group, Huawei, and LG Group in the intelligent vehicle sector extends beyond technological innovation in the vehicles themselves. It encompasses key supporting technologies such as communication technologies (e.g., H04L5, H04L27) and data processing.

2. Annual Application Trends of Key Core Technologies by Major Patent Assignees

The annual patent application trend of the number of key core technology patents among the top 10 patent assignees is shown in Figure 4. Most of these enterprises have exhibited a significant upward trend in the number of key core technology patents since 2015. The number of key core technologies of Toyota Motor Corporation is significantly higher than that of other enterprises, occupying a dominant position in this field.

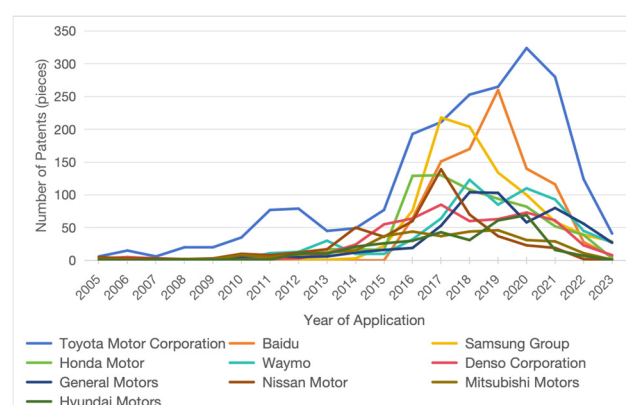


Figure 4. Annual Patent Application Trend of Top 10 Patent Assignees.

3. Competitive Strength of Major Patent Assignees

The H-index and patent citation rates of the top 20 patent holders are shown in Table 9 below. The table reveals that in the intelligent vehicle sector, traditional enterprises and specialized autonomous driving companies each hold distinct competitive advantages, while significant differences exist in the technological influence characteristics of enterprises across different countries. The high H-index of U.S. companies Waymo, Zoox, and Aurora Innovation demonstrates significant patent influence and strong competitive strength, securing the top three positions. Their annual citation efficiency and industry recognition also rank among the highest, with notable innovation and leadership in key core technologies. Traditional automakers like General Motors and Ford Motor Company also rank prominently, followed closely by Japanese automakers Toyota and Nissan. Among Chinese companies, only Baidu made it into the top ten. Overall, Chinese enterprises lag significantly behind their American and Japanese counterparts in H-index rankings, characterized by lower H-index values and weaker citation rates. Collectively, this

indicates that the technological influence of Chinese companies still has room for improvement. Hyundai Motor ranks tenth in H-index but exhibits a relatively low patent citation rate of 88.43. Samsung Group, despite ranking only 11th in H-index, achieves a citation rate of 271.5—far exceeding peers at its rank. This indicates that while Samsung’s overall patent accumulation in core intelligent vehicle technologies remains limited, its key innovations enjoy high recognition.

Table 9. Top 20 Assignees Ranked by H-Index.

Rank	Assignee (Country of Origin)	H-In- dex	Citation Rate ¹	Rank	Assignee (Country of Origin)	H-in- dex	Citation Rate ¹
1	Waymo (United States)	37	1442	11	Samsung Group (Republic of Korea)	10	271.5
2	Zoox (United States)	25	816	12	Motional (United States)	10	105.2
3	Aurora Innovation (United States)	22	355.6	13	Volkswagen (Germany)	9	76.29
4	General Motors (USA)	21	449.33	14	Denso Corporation (Japan)	8	63.14
5	Toyota Motor Corporation (Japan)	19	451.86	15	LG Corporation (Republic of Korea)	8	41
6	Nissan Motor (Japan)	16	165.78	16	Robert Bosch (Germany)	8	35.25
7	Honda Motor (Japan)	13	158.57	27	Mitsubishi Motors (Japan)	6	33.13
8	Baidu (China)	13	140.6	18	Huawei Technologies (China)	3	8.8
9	Ford Motors (USA)	13	91.71	19	Changan Automobile (China)	2	5.67
10	Hyundai Motors (Republic of Korea)	13	88.43	20	Apollo Intelligent Technology (China)	2	4.75

¹ Citation Rate = Total Citations of Core Technology Patents/(2024—Average Application Year of Core Technology Patents) Patent data spans 1950–2024, with the average application year calculated as the arithmetic mean of all core technology patent application years.

Overall, the dual-indicator analysis more clearly reveals the technological competitiveness gaps among enterprises of different types and nationalities: U.S. autonomous driving specialists lead global innovation in core intelligent vehicle technologies, combining comprehensive patent influence with high citation efficiency; Japanese traditional automakers maintain certain overall competitiveness through technological accumulation; Chinese companies, though achieving localized breakthroughs through leaders like Baidu, still lag significantly behind top-tier standards in both patent accumulation and innovation efficiency. This represents a critical direction for future breakthroughs in core technology R&D within China’s intelligent vehicle industry.

5. Discussion

This study identifies key core technologies in the intelligent vehicle sector through a dual-dimensional metric system evaluating technological significance and network characteristics. The findings align closely with the intelligent connected vehicle technology architecture previously interpreted at the World Intelligent Connected Vehicle Conference. From a technological perspective, the identified key core technologies encompass autonomous driving and vehicle control, intelligent transportation and vehicle–road coordination, onboard computing and data processing, as well as powertrain system integration and optimization. These align with the core architecture of autonomous driving technology—“perception-decision-execution”—validating the scientific rigor of the key core technology identification framework established in this paper. This also corresponds with the direction of recent industry technological advancements, reflecting the industry consensus on the transformation of intelligent vehicle technology toward data-driven algorithms.

The core technologies of intelligent vehicles are deeply intertwined with the sustainable development mechanisms of the transportation industry, forming a multi-dimensional green and low-carbon technical support system: autonomous driving and vehicle control technologies optimize operational efficiency, reducing per-vehicle energy consumption and emissions; intelligent transportation and vehicle–road coordination technologies alleviate congestion, enabling intensive utilization of road network resources; onboard computing and data processing technologies provide foundational data and intelligent decision-making support for the former two, ensuring the implementation of sustainable technologies. Power system integration and optimization technologies drive efficient application of new energy powertrains, reducing reliance on fossil fuels at the energy source. Synergistic efforts across these four domains advance sustainable development in the intelligent vehicle industry through operational, systemic, technological, and energy-related measures, establishing them as core technological drivers for green transformation in transportation.

Research findings indicate that among major competitive nations, China, the United States, Japan, Republic of Korea, and Germany dominate key core technology patents, accounting for 87.22% of global holdings. The overall proportion of key core technologies across nations exhibits a fluctuating upward trend, underscoring their critical importance in driving industrial advancement. China, the United States, and Japan hold significant patent portfolios in G08G1, B60W30, and G05D1 domains, reflecting their technological focus on vehicle control and interactive control systems with the traffic environment. The United States centers its patent strategy around G05D1 (autonomous vehicle control systems), while Republic of Korea also prioritizes R&D in wireless communication networks and digital information transmission technologies. The divergent R&D directions for key core technologies among major competitors reveal the characteristics of global division of labor within the intelligent vehicle industry, while also providing a cooperative foundation for the sustainable development of the global intelligent vehicle sector.

Beyond this, the United States holds a leading position in key core technologies by leveraging the synergistic advantages of its tech companies and traditional automakers. Autonomous driving companies like Waymo and Aurora Innovation focus on developing system-level solutions for autonomous driving, demonstrating significant patent influence and strong competitive strength. This advantage may partly stem from favorable U.S. testing regulations and ample capital support. The U.S. has successively issued multiple safety regulations for autonomous driving [43], permitting companies to conduct real-world road tests across state lines, thereby providing a permissive environment for technological implementation [44]. Japanese enterprises' development correlates with their longstanding expertise in automotive components and diverse partnerships [45]. China has achieved scale advantages in patent volume, accounting for 25.56% of global key core technologies. However, Chinese enterprises exhibit a "high patent volume, low H-index" pattern in critical smart vehicle technologies. Analyzing the distribution of patent volume and H-index across fields reveals this pattern is concentrated in application-oriented and supporting technology domains such as G08G1 (Vehicle–Road Environment Interaction Control Systems) and B60W30 (Vehicle Driving Control System Applications): Patents in these two domains account for over 40% of Chinese enterprises' total core technology patents, significantly bolstering their overall patent volume. Yet their H-index remains low, with average citations per patent substantially below the global average. The underlying reason is that Chinese enterprises have achieved rapid patent deployment leveraging industrial scale and policy guidance. However, these patents predominantly focus on R&D levels such as technological application optimization and scenario adaptation improvements. The proportion of original and core technologies is low, resulting in low

patent citation efficiency and relatively weak technological influence. This also points the way forward for subsequent technological upgrades.

Based on the above research findings and aligned with the needs of sustainable industrial development, the following targeted recommendations are proposed:

1. Increase investment in R&D for key core technologies: Intensify efforts in developing critical technologies such as autonomous driving, intelligent transportation and vehicle–road coordination, onboard computing, and powertrain integration. Allocate additional R&D funding with a strategic focus on breakthroughs in low-carbon and intelligent technologies, balancing short-term technical iterations with long-term fundamental research to solidify the foundation for technological innovation.
2. Improve patent quality and conversion efficiency: Guide enterprises and research institutions to focus on core technological pain points when planning patents. Encourage the application and authorization of high-value, high-stability patents, strengthening the systematic and forward-looking nature of patent planning. Simultaneously, promote the conversion of patented technologies into green production capacity and practical applications to enhance the sustainable value of patented technologies.
3. Strengthen the development of high-end innovation talent: Establish a dual-track talent system combining cultivation and recruitment. Partner with universities, research institutions, and leading enterprises to build practical training platforms for targeted cultivation of multidisciplinary talent in the intelligent vehicle sector. Simultaneously, implement specialized policies to attract top international technical talent, providing robust human capital support for technological innovation.
4. Deepen international collaborative innovation and cooperation: Actively participate in global technical standard-setting and cooperative projects within the intelligent vehicle sector. Establish regular cooperation mechanisms with leading international enterprises and research institutions, building platforms for technical exchange and resource sharing. Through collaboration, absorb advanced technological expertise and expand the international market presence of green technologies and products.
5. Optimize Policy Support and Safeguard Systems: At the governmental level, further introduce targeted policies to increase support for core technology R&D, patent portfolio development, and industry-academia-research collaboration. Improve intellectual property protection mechanisms and market supervision systems to foster a fair, orderly, and innovation-encouraging policy environment, thereby promoting high-quality and sustainable industrial development [46].
6. Promote Deep Industry-Academia-Research Integration and Technology Commercialization: Position enterprises as the primary innovation drivers, establish collaborative innovation platforms linking universities, research institutions, and industry, and focus joint research efforts on addressing practical industrial needs. Accelerate the iterative development and commercialization of core technologies, establish a closed-loop “technology-industry-market” system, and enhance overall industrial innovation efficiency.

6. Conclusions

Based on the definition and characteristics of key core technologies, this paper constructs a multidimensional identification indicator system for such technologies. Through empirical analysis of patent data in the intelligent vehicle sector, it effectively identifies the key core technologies in this field, providing precise technical positioning for sustainable industrial development. The study analyzes the global technological competition landscape at both national and corporate levels, proposing relevant recommendations to address shortcomings, enhance industrial core competitiveness, and advance low-carbon

sustainable transformation in the transportation sector. Theoretically, the comprehensive identification framework developed in this study offers a novel methodology for accurately identifying key core technologies in the intelligent vehicle sector, enriching research on technological innovation management. Practically, the findings provide valuable guidance for national governments, enterprises, and relevant institutions regarding R&D investment, resource allocation, and strategic planning in critical intelligent vehicle technologies. This research holds significant implications for advancing technological progress in the intelligent vehicle industry, fostering coordinated low-carbon development across the entire industrial chain, and supporting high-quality, sustainable economic growth.

The limitations of this study are as follows: First, this paper uses only mature patents as a reference for technological innovation. In practical applications, breakthroughs in key core technologies also involve the learning and application of abstract principles that are difficult to quantify. Therefore, future research could further consider the impact of other forms of scientific research achievements on industrial technological innovation and development. Second, constrained by the availability and statistical consistency of specialized R&D data for the intelligent vehicle industry, this study has not yet quantitatively analyzed the R&D efficiency of key core technologies across countries. Future research could leverage more detailed, standardized industry R&D data (e.g., R&D personnel scale, R&D funding investment, R&D outcome conversion efficiency) to introduce normalized metrics such as patents per capita and patent output per unit of R&D expenditure. This would enable deeper analysis of R&D efficiency and input–output characteristics for intelligent vehicle core technologies across nations, facilitating more thorough and equitable comparisons of technological competitiveness. Third, future research could integrate supplementary information such as corporate merger announcements and patent transfer databases to distinguish between patents developed through in-house R&D and those acquired through mergers. This would enable analysis of how different patent acquisition methods influence corporate technology portfolios, patent impact, and core competitiveness. Additionally, comparing patent portfolio formation strategies across different types of enterprises—traditional automakers, technology companies, and autonomous driving startups—would allow for a more refined analysis of technological competitiveness among intelligent vehicle enterprises.

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