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Classifying Invention Objectives of Electric Vehicle Chargers through Natural Language Processing and Machine Learning

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Abstract: The gradual adoption of electric vehicles (EVs) globally serves as a crucial move toward addressing global decarbonization goals for sustainable development. However, the lack of cost-effective, power-efficient, and safe chargers for EV batteries hampers adoption. Understanding the research needs and identifying the gaps in EV charger innovation informs investments and research to address development challenges. This study developed a unique text mining workflow to classify themes in EV charger technology and product development by analyzing U.S. patent award summaries. The text mining workflow combined the techniques of data extraction, data cleaning, natural language processing (NLP), statistical analysis, and unsupervised machine learning (ML) to extract unique themes and to visualize their relationships. There was a 47.7% increase in the number of EV charger patents issued in 2022 relative to that in 2018. The top four themes were charging station management, power transfer efficiency, on-board charger design, and temperature management. More than half (53.8%) of the EV charger patents issued over the five-year period from 2018 to 2022 addressed problems within those four themes. Patents that addressed wireless charging, fast charging, and fleet charging accounted for less than 10% each of the EV charger patents issued. This suggests that the industry is still at the frontier of addressing those problems. This study further presents examples of the specific EV charger problems addressed within each theme. The findings can inform investment decisions and policymaking to focus on R&D resources that will advance the state of the art and spur EV adoption.

Keywords: EV charging safety; EV charger reliability; natural language processing; unsupervised machine learning

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1. Introduction

The worldwide push to address decarbonization goals focuses on replacing internal combustion engine (ICE) vehicles with electric vehicles (EVs). The movement has created both opportunities and challenges [1]. Some of the key opportunities include vehicle cost reduction due to fewer parts and lower maintenance cost from the elimination of items like fuel pumps, coolants, engine oils, hydraulic liquids, spark plugs, and moving parts along the drive train [2]. However, a key challenge in the adoption of EVs is the insufficient availability of accessible, dependable, interoperable, efficient, and affordable battery charging facilities [3]. Research has found that aside from government subsidies, positive experiences with EV chargers can encourage their adoption [4]. Analysts predict that up to 42 million EVs will be on U.S. roads by 2030, generating the need for up to 35 million charging ports [5]. Consequently, the U.S. bipartisan infrastructure bill signed into law in 2021 allocated USD 5 billion to help states build an EV charging infrastructure.

Batteries are the most expensive items on EVs, so they dominate both the vehicle price and repair costs [2]. Therefore, it is critically important that charging a battery does not degrade its life cycle [6]. Consumers also expect that charging an EV at a dedicated facility should take no longer than refilling the gas tank of an ICE vehicle [7]. However, the current state of the art exhibits a tradeoff in charging speed and battery life degradation [8]. Therefore, the industry must conduct more research to find alternative solutions.

The goal of this study is to classify the invention objectives of EV battery charger technology development and to gain insights about the development trends and types of technical challenges that researchers are still addressing. Insights into the specific EV charger problems that inventors have been addressing will inform investment decisions and policymaking to focus on research and development (R&D) resources. Summarizing the academic literature alone cannot expose the breadth of practical solutions to commercialize new EV charging technologies. Therefore, this research employed a different approach, which was to analyze trends in patent activity. Companies file patents to protect their freedom to commercialize a technology and to maintain a competitive advantage in product sales. Therefore, patents can be a reliable indicator of problems that companies are addressing to commercialize innovative products [1].

The contribution of this study is a unique text mining workflow to classify themes in EV charger technology and product development, thus identifying specific problems that companies are addressing toward commercialization goals. The text mining workflow combines techniques of data extraction, data cleaning, natural language processing (NLP), statistical analysis, and unsupervised machine learning (ML) to extract unique themes and to visualize their relationships.

The organization of the rest of this paper is as follows: Section 2 reviews the literature on EV charger development, including infrastructure characteristics, charger architectural choices, fast charging, and wireless charging research. Section 3 describes the hybrid text mining workflow developed to address the goal of this research. Section 4 discusses the analytical results and the relationship among themes identified from the patent objectives. Section 5 concludes the analysis and suggests future work.

2. Literature Review

The literature on EV chargers is extremely broad, and the technology and standards continue to evolve. For instance, at the time of this writing, the major automotive industry players like GM, Volvo, Ford, and Nissan have adopted the Tesla charging standard [9]. Therefore, to reflect the current state of the art, this literature review will focus only on findings from articles recently published. The next subsections review developments in the EV charging market, infrastructure, circuit design, fast charging, and wireless charging.

2.1. Charger Market

Studies have consistently found that aside from government subsidies, a positive experience with EV chargers can increase the propensity to purchase EVs [4]. A recent study posited that the lack of charger availability and their unreliable operation has been impeding their adoption [10]. This suggests that companies are still trying to address certain underlying challenges in EV charger design for reliable operation and widespread deployment. The scholarly academic literature does not yet provide sufficient insights into the underlying causes for poor charger reliability and availability. Therefore, a few researchers adopted the strategy of analyzing patents to uncover insights into the underlying challenges that companies are still addressing. Choi (2018) suggested that patenting activity can be a robust indicator of technology development trends [1]. Phirouzabadi et al. (2020) also supported the notion that patent bibliometrics data can inform applied R&D activities in a knowledge domain such as the evolution of vehicle powertrain technologies [11].

The enormous size and unstructured format of patent databases complicates their analysis to distill knowledge about the specific objectives of inventions in a knowledge domain. Only a few articles, consequently, analyzed patent databases to discover trends in challenges that companies are addressing. For instance, Yuan and Wu (2020) analyzed battery development trends for EVs and found that the key technologies focused on solving problems related to battery heating, battery cooling, and charging methods [12]. Ma et al. (2022) analyzed patents about EV development from 1970 to 2016 and found that topics related to safely and quickly charging a battery and contactless charging are becoming a research frontier [3].

Yuan and Li (2021) found that companies filed 93.94% of priority patent applications at the Japan Patent Office (JPO), the China National Intellectual Property Administration (CNIPA), the U.S. Patent and Trademark Office (USPTO), the German Patent and Trademark Office (GPTO), and the Korean Intellectual Property Office (KIPO) but less than 6% in France, the U.K., or other countries [13]. Analysis of the scholarly academic literature found that studies reviewed trends in EV infrastructure development, circuit design, fast charging, and wireless charging. The next subsections summarize some of the key findings.

2.2. Charger Infrastructure

Bommana et al. (2023) comprehensively reviewed EV charger topologies and characteristics [14]; and Acharige et al. (2023) separately reviewed standards, architectures, and converter configurations [6]. Table 1 summarizes the information gleaned from both articles. Chargers are available in four levels based on the duration required to charge the battery with 20 to 50 kWh of energy. Chargers are either on-board or external to the vehicle. The Society of Automotive Engineers (SAE) published several standards that define various aspects of EV chargers such as their general physical, electrical, communication protocol, and performance requirements.

Table 1. EV charger characteristics and standards [6,14].

Category	Type	Power Source	Charge Time	Standards
Level 1 (Slow)	On-board	Standard Outlet	4 to 36 h	SAE J1772, IEC 62196-2, IEC 61851-22/23, GB/T 202-34-2
Level 2 (Medium)	On-board	Dedicated Equipment (breaker in cable)	1 to 6 h	SAE J1772, IEC 62196-2, IEC 61851-22/23, GB/T 202-34-2
Level 3 (Fast)	Off-board	Dedicated Equipment (communication and event monitoring)	0.4 to 1 h	IEC 61851-22/23, IEC 62196-2
Extremely Fast	Off-board	Dedicated Equipment (communication and event monitoring)	5 min	IEC 62196, SAE J2836/2, SAE J2847/2

Faustino et al. (2023) presented a methodology to increase the utilization of chargers per station by defining and allocating charging zones [15]. Khamis et al. (2023) proposed a charging strategy that utilized demand-side management to allocate power in the EV charger network [16]. Johnson et al. (2022) surveyed publicly disclosed EV charger vulnerabilities to cyber-attacks and suggested the vendors must incorporate continuous processes to harden their deployed infrastructure and conduct regular vulnerability assessments [17]. Al Attar et al. (2023) reviewed switching control strategies to enable bidirectional power transfer between vehicles and the electric power grid. They classified control strategies as either linear or non-linear [18]. Each control strategy presented had its advantages and limitations in terms of performance, size, and cost.

2.3. Charger Circuit Design

Vishnuram et al. (2023) conducted a comprehensive review of EV power converter topologies and found that there are many types of implementations, each with advantages and disadvantages in performance, size, and cost [19]. In a similar review, Ali et al. (2023) classified power electronic converter (PEC) topologies into the four possible quadrants of AC and DC converters: DC-DC, DC-AC, AC-DC, and AC-AC [8]. They identified ongoing challenges as power conversion losses, bulkiness, and electromagnetic interference. Thanakam and Kumsuwan (2023) designed a phase-locked loop (PLL) control method to enhance the quality of bidirectional power transfer in EV chargers [20].

Berrehil El Kattel et al. (2023) reviewed the implementation of battery charger structures and found that they classify into either on-board or off-board embodiments that implement either unidirectional or bidirectional power transfer by incorporating either isolated or non-isolated AC-to-DC conversion stages [21]. Karneddi and Ronanki (2023) presented the design of a charger that can be reconfigured to charge multiple types of battery packs requiring different voltage levels [22]. Gupta et al. (2023) presented the design of an on-board charger that can charge multiple EVs using multiple outputs [23]. Na et al. (2019) reviewed and classified the topologies of on-board EV chargers into three groups based on the components integrated with the vehicle traction motor system [24]. On-board chargers must normally communicate information to the charging source, such as the current charge state and end-of-charge time preference [25]. The study proposed an adaptive voltage-feedback controller for an on-board EV charger that obviates the need for real-time communications with the power source.

2.4. Fast Charging

Polat et al. (2023) noted that consumer expectations for the speed of recharging an EV to be the same as that for refilling an ICE vehicle tank will increase the demand for fast chargers [7]. Deploying more fast chargers, however, increases the load burden on the electric grid during times of peak demand. Therefore, researchers recently proposed that fast charging incorporate a battery energy storage system (BESS) with controls for cooling to even out the load burden. Pradhan et al. (2023) conducted a comprehensive review to identify the system level and use case-related challenges in transitioning on-board chargers to recent fast charging standards [26].

2.5. Wireless Charging

Song et al. (2023) found that although wireless charging for mobile devices and wearable equipment is widespread, the technology is still a developing trend for EV applications, and interoperability requirements are still undefined for high power levels [27]. Dimitriadou et al. (2023) categorized wireless power transfer as using either far-field or near-field methods, with each having advantages and disadvantages, as summarized in Table 2 [28].

Table 2. Classification of wireless charging methods.

	Methods	Advantages	Disadvantages
Far-Field	Microwave	• Can transfer energy over long distances.	• Poor efficiency. • Risk of hazardous human exposure to radio frequencies. • Requires bulky antennas.
	Optical (Laser, Light)		• Poor efficiency. • Risk of optical disturbances or even blindness. • Unidirectional power flow.
	Acoustic-Based		• Poor efficiency. • Limited to low power levels.
Near-Field	Capacitive	• High-frequency electric field allows for efficient transfer.	• Requires proximity between transmitter and receiver. • Limited to low power levels.
	Inductive	• Safe and user-friendly. • Modest maintenance costs due to absence of mechanical parts.	• Requires proximity between transmitter and receiver. • Efficiency may decrease with misalignment.

Vishnuram et al. (2023) classified wireless charging systems more broadly as either static, where the vehicle charges while parked, or dynamic, where the vehicle charges while moving [29]. The main advantages of dynamic wireless charging include convenience and the potential for vehicles to use smaller batteries, which would reduce both their weight and cost. The main disadvantages of dynamic wireless charging are higher infrastructure costs and lower power transfer efficiency. Yang et al. (2023) discussed how in-pavement wireless chargers can dynamically charge vehicles as they move [30]. However, current methods require continuous operation at full power, which causes large standby currents and concerns of exposure to harmful electromagnetic radiation. The authors proposed an approach to automatically contain field exposure to reduce the radiated emissions.

3. Methodology

The next two subsections describe the dataset utilized and the NLP workflow developed in this study to analyze and visualize the results. Figure 1 shows the NLP workflow of the methodology as three distinct procedure collections: data filtering, relevance filtering, and theme identification.

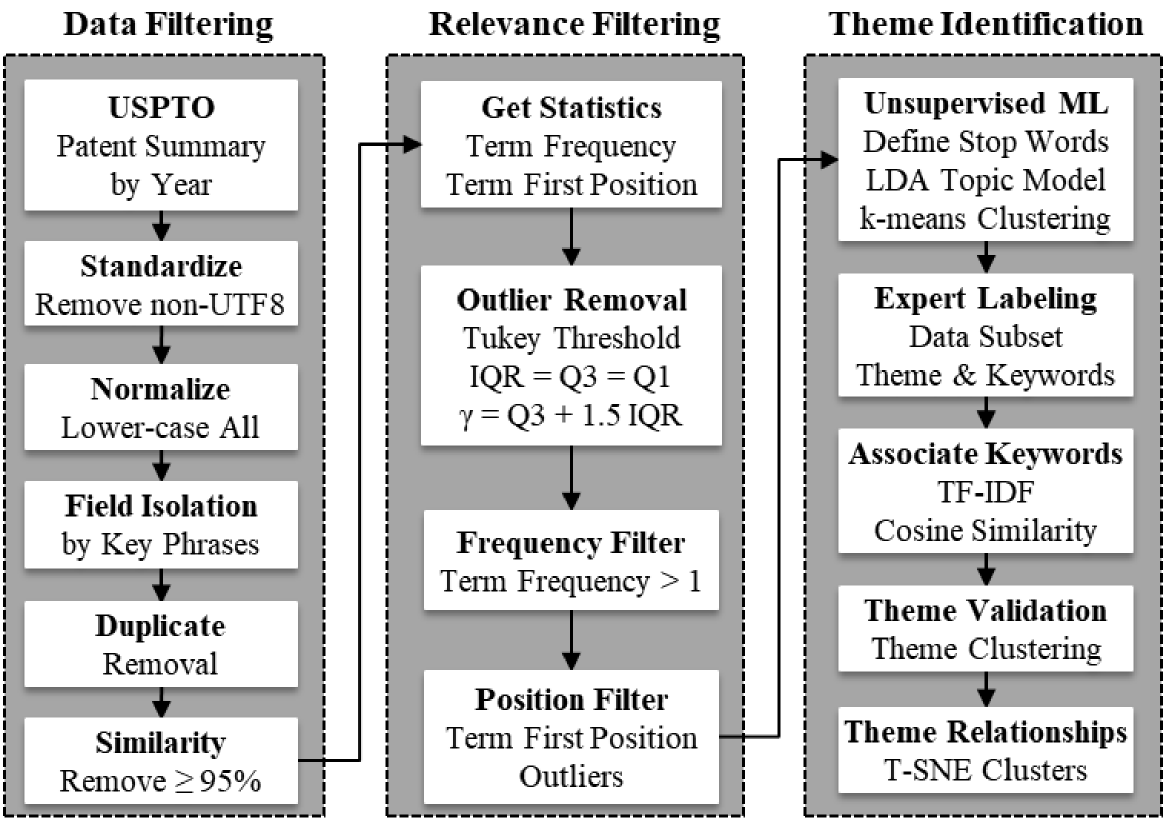

Figure 1. The NLP workflow.

3.1. Data and Cleansing

According to the World Intellectual Property Organization (WIPO) statistics database, China and the United States have consistently filed the highest number of patents in the world [31]. The U.S. has outpaced China in patent applications published in the computer technology field. Furthermore, the United States Patent and Trademark Office (USPTO) maintains one of the most comprehensive, updated, and easily accessible patent databases in the world. Therefore, this research focused on the USPTO database, which comprises annual summaries of the patents granted [32]. The data entry for each year is a tab-separated value (TSV)-formatted file that contains a column with the patent number and a second column with the summary text. The summary text averaged a word count of 2098 and a standard deviation of 5328. Curiously, the patent summaries did not include the title or abstract of the patent. Also, the patent summaries did not have a regular structure of subheadings. Most of the summary texts had a "background" or an "introduction" subsection followed by a "summary" subsection. A few of the summaries contained one or more sentences that described the "field" and/or the "objects" of the invention. Several descriptions cross-referenced related patent applications, many granted by countries outside of the United States.

The series of data filtering procedures employed by this study extracted the patent summaries from 2018 to 2022 that focused on EV charger development. The "Standardize" procedure assured that all characters in the corpus were UTC-8-encoded to prevent downstream procedures from encountering unrecognized character encodings during tokenization. The "Normalize" procedure lower-cased all words in the corpus so that searching for a phrase would be case-insensitive. Subsequently, the "Field Isolation" procedure retained patent summaries that focused on the field of EV charger design by identifying documents that contained a union of the following set of key phrases: ("electric vehicle", "charger", "battery").

Post-isolation revealed several duplicate and similar patent summaries even though they described different patents, as distinguished by a unique patent number. The reason for the duplicate or highly similar patent summaries was that the filing organization modified or updated one or more claims of a patent but filed it as a new patent. However, the patent summary did not mention specific claims of the new patent but used the same or a similar summary. Removing highly similar documents in the corpus required a measure of "similarity" and defining a threshold for their removal. To do so, the "Cosine Similarity" procedure computed a similarity matrix for all document pairs as

$$\cos(\theta) = \frac{\sum_{i=1}^{n} X_i Y_i}{\sqrt{\sum_{i=1}^{n} X_i^2}\sqrt{\sum_{i=1}^{n} Y_i^2}} \tag{1}$$

where X and Y are vector representations of each document, and n is the number of features in each vector. The workflow used an NLP vectorization technique to represent each document as a numerical feature vector. Prior to vectorization, a text cleaning procedure removed numbers, punctuation, accented words, quotation symbols, mathematical operands, website addresses, and 'stop' words from the corpus. Stop words such as "and", "the", and "it" occur frequently among individual documents, so they do not contribute toward distinguishing among documents. The tokenization procedure then built a "dictionary" containing all the unique words in the corpus. The numerical encoding for each word was its position in the dictionary [33].

After tokenization, a term frequency–inverse document frequency (TF-IDF) vectorizer represented each document as a sparse vector containing a TF-IDF score $W_{t,d}$, which was

$$W_{t,d} = F_{t,d}\left[\log\left(\frac{N}{D_t}\right) + 1\right] \tag{2}$$

The variable $F_{t,d}$ is the term frequency (TF) for term t in document d. The remainder of the equation is the inverse document frequency (IDF), where D_t is the number of documents in the corpus of N documents that contained term t. Intuitively, the variable $F_{t,d}$ represents the importance of a term associated with a document, and the IDF scales down that importance based on the term's commonality across the documents in the corpus [34].

Given the TF-IDF-vectorized representation of each document, the cosine similarity procedure computed a matrix of pairwise similarity with cell entries ranging from zero to unity. A geometrical interpretation is that the angle between feature vectors of identical documents are zero, yielding a cosine value of unity. The feature vectors of dissimilar documents point in orthogonal directions (90 degrees), yielding a cosine value of zero. The similarity procedure then extracted the maximum cosine similarity for each document and removed those with scores greater than 95%. Selecting the 95% threshold mirrored the customary p-value for statistical significance when comparing membership in distributions. An examination of similar documents confirmed that they contained only minor word differences or different spellings of the same word.

3.2. Relevance Filtering

Empirical examination of the documents isolated based on their containing the key phrases revealed that some did not primarily focus on the design of EV chargers but had only a mild relevance to the field. Empirical observation determined that documents with mild relevance to the field contained only a single mention of a key phrase. For example, patents that mentioned the key phrase "electric vehicle" only once described an invention that could benefit electric chargers, but that was not the primary focus. A second empirical observation was that mildly relevant documents mentioned a key phrase toward the end of the document. Therefore, the methodology required further "relevance filtering" to focus the patent summaries on charger systems that targeted EVs.

The relevance filtering procedures of the NLP workflow removed invention summaries with low relevance to EV charging. The threshold for elimination based on the frequency of occurrence was a single mention, and that based on first position of mention was the distribution outlier. The outlier threshold γ was determined from the John Tukey rule of interquartile range [35] where

$$\gamma = Q_3 + 1.5 \times [Q_3 - Q_1] \quad (3)$$

Q_1 and Q_3 are the first- and third-quartile values, respectively. The first quartile and third quartile are the sorted word positions of the first mention of a key phrase for the first 25% and 75% of the documents, respectively.

3.3. Theme Identification

The goal of the theme identification section of the NLP workflow was to classify patent summaries into unique themes based on the specific objectives of the invention. Mature state-of-the-art topic modeling techniques such as latent Dirichlet allocation (LDA) attempt to discover abstract topics in a corpus by applying unsupervised machine learning (ML) methods. Current methods cluster documents by their TF-IDF vectors. However, the procedure requires setting a hyperparameter for the number of topic clusters, which involves heuristics and subjectivity. This study took a more objective approach by first setting many topics, such as half the number of documents, and then applying k-means clustering to calculate the number of clusters that maximized a silhouette score. A silhouette score measures how similar an object is to its own cluster compared with other clusters. LDA produced N topics as a vector of TF-IDF scores for each document. Then, we k-means-clustered the documents by using the TF-IDF vectors as features. The procedure then iteratively reduced the number of LDA topics until it equaled the number of k-means clusters that maximized the silhouette score.

This study improved the performance of the LDA by defining and removing additional domain-specific stop words. To do so, the author applied the bag-of-words NLP technique to identify all keywords, excluding the standard stop words removed by the text cleaning procedure. The author then identified domain-specific stop words such as "invention", "prior art", "claim", "disclosure", "method", "apparatus", "patent", "application", and "embodiment". The key phrases used to isolate relevant patents were also stop words because they must appear in all documents. Table 3 summarizes the various methods and metrics utilized in the NLP workflow. Aggarwal's book (2015) provides a good overview of the data mining concepts [34], and the book by Lane et al. (2019) explains the functionality of the NLP methods used in the workflow [36].

Table 3. Summary of the methods and metrics utilized in the NLP workflow.

Method	Functionality	Benefits	Limitations
Tokenization	Splits text into smaller pieces, commonly known as tokens, such as words or subwords.	• Essential for text preprocessing • Enables easier mapping of text to a more structured form • Facilitates text analytics and feature extraction	• May lose contextual meaning • Language-specific rules may apply
Lemmatization	Reduces inflected forms of words to their base form.	• Reduces dimensionality • Improves computational efficiency	• May lose some contextual information
TF-IDF Vectorization	Represents the importance of terms in each document for clustering.	• Effective for document similarity • Widely used in text mining	• Sensitive to document length • Does not capture semantic meaning
Cosine Similarity	Measures the cosine of the angle between two vectors to determine similarity.	• Effective for high-dimensional data • Scale-independent	• Does not consider the magnitude of vectors
Latent Dirichlet Allocation	Classifies text into abstract topics using unsupervised machine learning.	• Does not require labeled data • Can handle large datasets	• Requires setting a hyperparameter for the number of topic clusters • Lack of topic specificity
Bag-of-Words	Represents text data as a "bag" of its words, disregarding grammar and word order.	• Simple to understand and implement • Effective for document classification	• Loses all information about word order • Sensitive to vocabulary size
k-means Clustering	Groups documents into clusters that maximize a silhouette score.	• Efficient for large datasets • Easy to implement	• Requires the number of clusters to be specified • Sensitive to initial conditions
Silhouette Score	Measures how similar an object is to its own cluster compared to other clusters.	• Provides insight into the distance between resulting clusters • Useful for selecting the number of clusters	• Computationally expensive for large datasets • May not work well for non-globular cluster shapes
Expert Theme Identification	Utilizes subject matter expertise to identify unique themes and associated keywords.	• Highly accurate • Tailored to specific objectives	• Time-consuming • Requires domain knowledge
t-SNE	Visualizes high-dimensional data by giving each datapoint a location in a two-dimensional map.	• Effective for visualizing complex data structures • Preserves local and global structure	• Computationally expensive • Not deterministic

Documents classified within each LDA topic required inspection by a subject matter expert (SME) to define a unique theme reflecting the main objective of the invention. The SME also extracted associated keywords from a document that uniquely reflected the patent objective. Subsequently, the "Associate Keywords" method attempted to assign an associated SME-identified theme to the remaining documents based on the set of unique themes and their associated keywords identified so far. The SME then examined the documents that the keyword association method could not assign a theme to in order to identify another unique theme or to identify a set of unique keywords associated with a previously identified theme. This procedure continued until the method assigned an SME-identified theme to all documents.

Identifying unique themes and associated unique keywords leveraged the author's educational background in electrical engineering, experience designing power control circuits, and patenting experience. Expert theme identification required knowledge of a generalized architecture for EV charger systems. Figure 2 shows the authors' interpretation of the functional block diagram for a generalized unidirectional EV charger system. A design for bidirectional charging would include another circuit pathway from the battery back to an AC output. Actual designs may use only portions of the architecture shown, and the specific implementation of each sub-function will vary in terms of the circuit design and component selection.

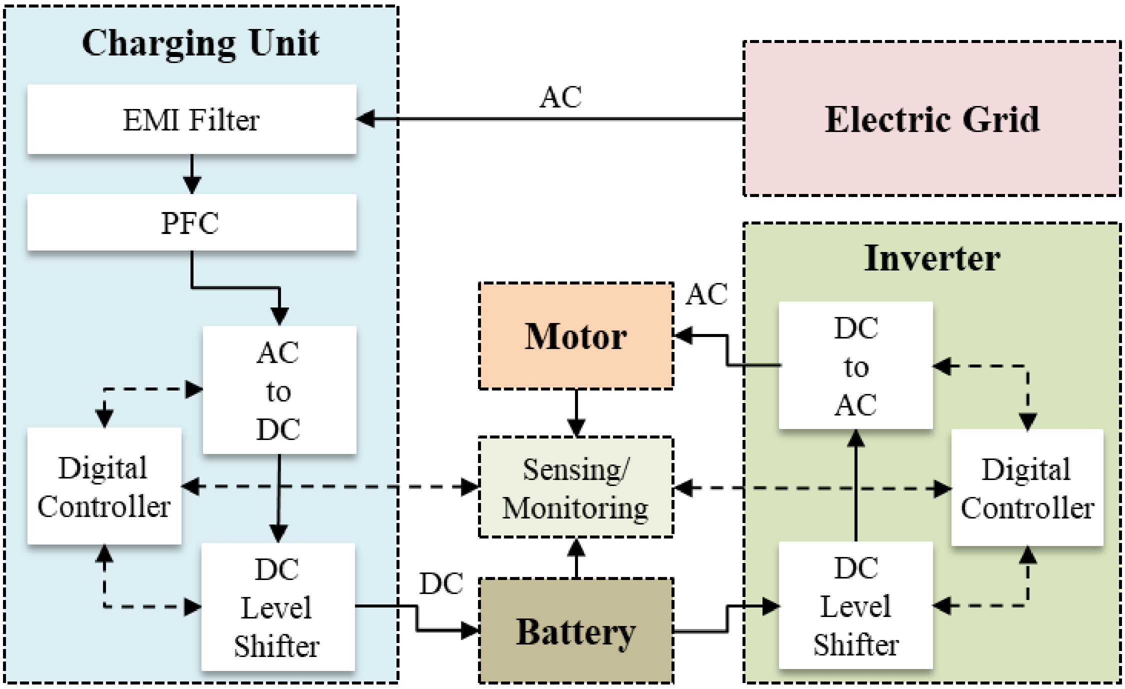

Figure 2. Generalized architecture of a unidirectional EV charging system.

The general architecture for a unidirectional EV charging system includes a unit that connects to an AC power source, a battery, a motor, and an inverter that converts energy from the battery to power the motor. The solid arrows represent voltages and currents, and the dashed arrows represent control and feedback signals. The charging unit can be outside or inside the vehicle. The charging unit may include electronic circuits and a digital controller to filter the AC power for reduced electromagnetic interference (EMI) and to employ power-factor correction (PFC) techniques to purify the harmonics of the input power source. An AC-to-DC converter and a DC level shifter produces the voltage and current that a particular battery requires for charging.

Sensors monitor the charge status, temperature, voltage, current, motor operation, and other characteristics of the system or components. The inverter converts DC voltage from the battery to the appropriate AC voltage and current required to drive the motor.

The topic modeling technique assigned themes based on the unique keywords associated with each unique theme. For each document, the topic modeler accumulated the cosine similarity between the document's TF-IDF-vectorized representation and the TF-IDF-vectorized representation of each keyword associated with a unique theme. Therefore, each document was associated with a vector containing an accumulated cosine similarity for each of the unique themes.

To reduce the computational burden, the vectorization algorithm converted words to lemmatized tokens for both the document and the keywords associated with each unique theme. Lemmatization reduced the inflection forms of a word to its linguistic base or lemma by doing both vocabulary and morphological analyses. Therefore, lemmatization reduced the number of word forms, which minimized the length of the TF-IDF vector representing each document to improve the computational efficiency.

The "Theme Validation" procedure clustered documents by the feature vectors containing the accumulated cosine similarity scores for each theme. The goal was to evaluate the performance of the topic model theme assignment by observing that the document clusters had a single maximum similarity score with a unique theme. Subsequently, the "Theme Relationships" procedure generated a visualization of how documents clustered within a theme and how theme clusters related to each other in feature space. The technique utilized the t-distributed stochastic neighbor embedding (t-SNE) manifold method to reduce the feature space of the themes to two dimensions [36].

4. Results and Discussion

The following subsections discuss the results of the NLP workflow: data filtering, theme identification, and theme relationships.

4.1. Data Filtering

Table 4 summarizes the results of the data extraction and filtering for each year of the dataset. The average number of patents issued per year was 327,545 with a standard deviation of 28,213. The average number of patents that contained all three key phrases was 247 with a standard deviation of 18. Therefore, patents relating to EV chargers, on average, accounted for less than 0.1% of all patents issued over the five-year period.

Table 4. Results of the data isolation and data filtering procedures of the NLP workflow.

Procedure	2022	2021	2020	2019	2018
USPTO Summaries	283,075	330,645	355,647	357,790	310,568
Isolate Patents	275	228	234	261	235
Duplicate Removal	256	225	232	259	234
Similarity Reduction	245	217	232	256	234
Frequency Filter	120	95	107	108	92
"electric vehicle" T (C)	≤272 (108)	≤275 (83)	≤192 (93)	≤231 (96)	≤309 (81)
"charger" T (C)	≤811 (104)	≤975 (77)	≤853 (90)	≤711 (90)	≤872 (72)
"battery" T (C)	≤301 (96)	≤193 (69)	≤288 (78)	≤243 (82)	≤288 (65)

The patent summaries for some years contained only a few duplicates and a few similar patent descriptions. Applying the document relevance filters further reduced the corpus size by an average of 56%. The last three rows of Table 4 lists, for each key phrase of the invention field, the outlier position threshold (T) and the count (C) of the documents remaining after removing those outliers. Figure 3 shows the distribution of counts and first-position mentions for each key phrase. The inset of each sub-figure is a box plot showing the statistics of the distributions prior to filtering. The foreground plots show the distribution after filtering. For example, Figure 3a shows that prior to outlier removal, the phrase "electric vehicle" had a mean count of 6.78, a standard deviation of 11.4, a median of 3, the first quartile (25%) beginning with a frequency of 1, and the third quartile (75%) ending with a frequency of 7. The median was consistently less than the mean due to the high skew of the distributions. Figure 3b shows that the statistics for the term "charger" closely followed those for the term "electric vehicle", suggesting that the distribution of their co-occurrence frequency was similar. That is, the patent summaries tended to mention both terms with similar frequencies, which validated their high relevance to EV chargers. On average, Figure 3c shows the term "battery" occurred approximately three times more than the other two terms. This further validated their relevance to EV battery chargers.

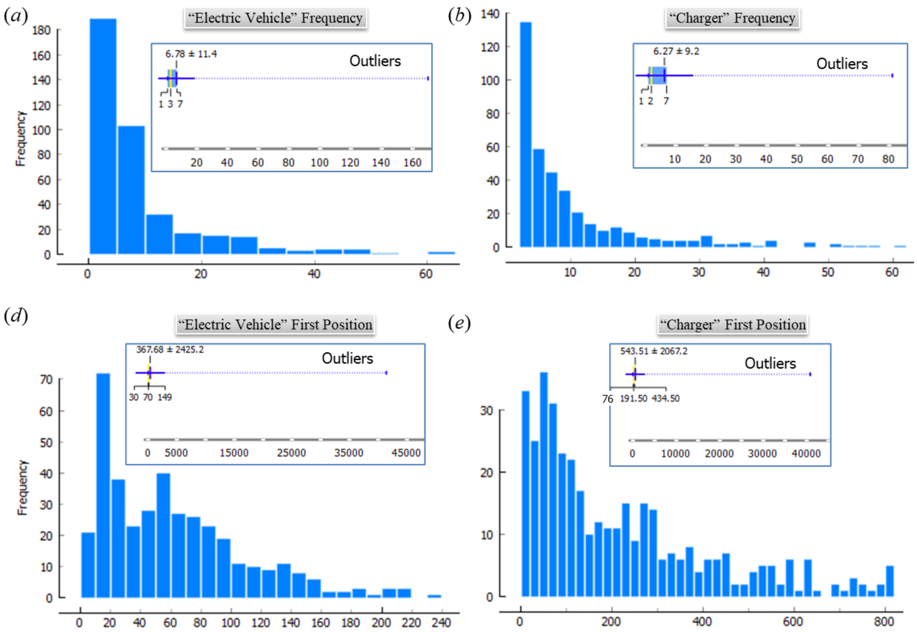

Figure 3. Frequency and position distribution of invention field keywords after outlier elimination.

Figure 3d–f show the prior and post-filtered position distributions of the first mention of the phrases "electric vehicle", "charger", and "battery", respectively. On average, the patent summaries mentioned the term "battery" earlier than the other two phrases but within 123 words of the term "electric vehicle", which further highlighted the relevance of the patent summaries to EV battery chargers.

4.2. Theme Identification

The author selected the 96 patent summaries from the year 2022 as the subset for expert theme identification to assure coverage of all the potential unique patent objectives appearing within a year. Table 5 shows the themes identified after reading and comprehending a subset of patent summaries. The table lists exemplary invention objectives within each theme. Comparing the LDA topic classification results with the human expert theme identification post-analysis revealed only some agreement. LDA did not adequately capture the specific objectives of each invention. Instead, LDA clustered documents based on the similarities of their TF-IDF vectors rather than the strength of their association with unique keywords that distinguished the patent objectives. Consequently, LDA clusters tended to capture broader themes of the inventions rather than the specific objectives. For example, Figure 4 shows a hierarchical relationship among the themes where LDA could sometimes distinguish among the broader topics like circuit design versus operations management but not narrower objectives such as power transfer efficiency versus fast charging, with both relating to an aspect of circuit design.

Table 5. Invention themes, broad objectives, and associated keywords extracted.

Theme	Broad Invention Objectives	Extracted Keywords
Charge Scheduling	Optimizing charge schedule and amount based on battery charge level, battery temperature, time of day, selected routes, environmental factors, and expected drive distance. Assigning parking spaces with chargers based on vehicle type, charging needs, and expected charge time. Predicting fleet dispatch times based on charging level and charging needs. Autonomous mobile chargers scheduled to arrive and charge vehicles in a parking facility.	travel, scheduled, smart parking, placement, surge, dispatch prediction, navigation, depletion, arrival, day, session
Charge Station Management	Portable and mobile charging stations to balance grid capacity, vehicle-to-vehicle chargers, security countermeasures in battery swapping, charging from external batteries, payment system integration.	dock, station, amount, authentication, mobile, removal, external, movable, swapping, automated, autonomous, money
Charging Controller	Control switching duty cycle to improve voltage or current conversion. Control charge speed, overvoltage, standby current, surge current, line noise, battery impurity removal, DC-to-AC conversion to charge from a battery, and voltage level based on vehicle needs. Remote control of charger.	signal processing, overvoltage, shock, pulse width modulation, PWM, controlling, request, power-line communication, PLC, battery life, inrush, testing, post
Charging Safety	Preventing electrical shocks, reducing drain current, reducing cable stress, and preventing short circuits.	leakage, drain, protection, abnormal, burning, short-circuit, gap extrusion, danger, safe, stiffness
Fast Charging	Methods of increasing charge speed by circuit design and the selection of components, materials, battery chemistry, and charge control techniques.	fast charger, rapid, quickly, faster, aluminum
Fuel Integration	Combining various means of charging a battery, including the integration of other fuel types, turbines, and charge reservoirs.	hydrogen, fuel, gas, turbine
Multiple Vehicle Charging	Charger sharing systems, charge reservation systems, fleet charging, and auxiliary chargers like robotic following charging systems.	between vehicle, unmanned, multiple electric, sharing, mutual
On-board Charger	Various techniques for designing chargers that a vehicle can carry or integrate. Methods include size reduction techniques, kinetic charging from vehicle motion, and electric circuit design to improve charging efficiency and to receive various levels of AC and DC voltages, including inductive coupling.	on-board, onboard, onboard charger, OBC, generator
Power Transfer Efficiency	Various means of improving power transfer efficiency among chargers, batteries, and motors. Methods include circuit design, component selection, power factor correction, charge storage, and electronic control of switching elements.	active filter, regulate, zero voltage switching, ZVS, power factor correction, PFC, ripple, 3-phase, three-phase, boost, rectify, synchronous, resonant, size
State Monitoring	Means of evaluating the state of a charger, vehicle, and battery to inform methods of power transfer optimization and charging needs. Customizing charge status indicators and integrating status with cloud monitoring systems. Automatically connecting and disconnecting chargers based on charge status.	status, monitor, state, measure, life, timeout, deterioration, detecting presence, state-of-charge, health
Temperature Management	Controlling and/or evaluating the temperature of a charging cable and/or a battery to protect component health, optimize charging efficiency, and increase the accuracy of charging systems.	cool, heat, temperature, thermal, coolant, refrigerant, ventilating, chiller, cooling a charger, overheat
Wireless Charging	Contactless charging a battery by inductive or wireless power transfer. Autonomous navigation to wireless charging systems. Design of wireless chargers.	wireless, inductive, wireless power transfer, WPT

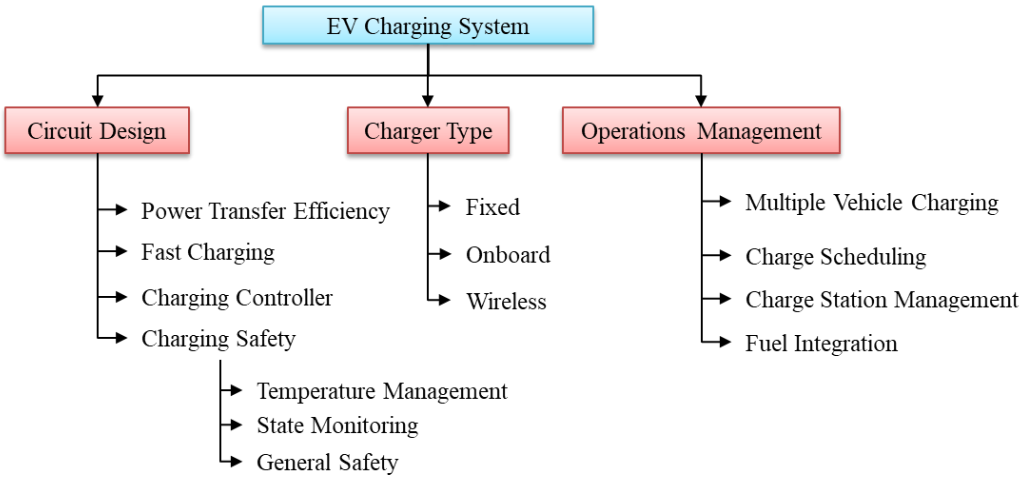

Figure 4. Hierarchical relationship among themes in EV charger inventions.

Although LDA was imperfect, its inclusion in the NLP workflow provided some value in that a manager can divide the task of unique theme identification and keyword extraction among persons with different areas of high-level expertise, such as circuit design versus operations management. It is also possible in the future to use large language models (LLMs) that support an application programming interface (API) to identify the objectives of patents and to help humans classify them into unique themes. However, LLMs currently have the problems of inaccuracy, temporal knowledge gaps, and hallucinations [37]. This means that human feedback is necessary to verify the accuracy and appropriateness of every LLM response, thus adding an additional layer of labor.

Table 6 summarizes the distribution of patents by theme and by year issued. Figure 5 plots the data in Table 6 for visualization. There was a 47.7% increase in the number of EV charger patents issued in 2022 relative to that in 2018. The top four themes accounted for more than half (53.8%) of the EV charger patents issued over the five-year period.

Table 6. Theme distribution.

Theme	2018	2019	2020	2021	2022	Total	% Theme	% Acc
Charge Station Management	15	9	16	20	6	66	16.9%	16.9%
Power Transfer Efficiency	12	11	9	7	15	54	13.8%	30.8%
On-board Charger	8	7	11	7	14	47	12.1%	42.8%
Temperature Management	2	13	9	7	12	43	11.0%	53.8%
State Monitoring	5	8	6	11	10	40	10.3%	64.1%
Charging Controller	7	4	8	5	12	36	9.2%	73.3%
Charge Scheduling	10	7	1	3	9	30	7.7%	81.0%
Wireless Charging	5	9	6	2	8	30	7.7%	88.7%
Charging Safety	1	7	2	2	4	16	4.1%	92.8%
Fast Charging	0	2	6	1	2	11	2.8%	95.6%
Fuel Integration	0	4	3	0	2	9	2.3%	97.9%
Multiple Vehicle Charging	0	1	1	4	2	8	2.1%	100.0%
Annual Total	65	82	78	69	96	390	100.0%	

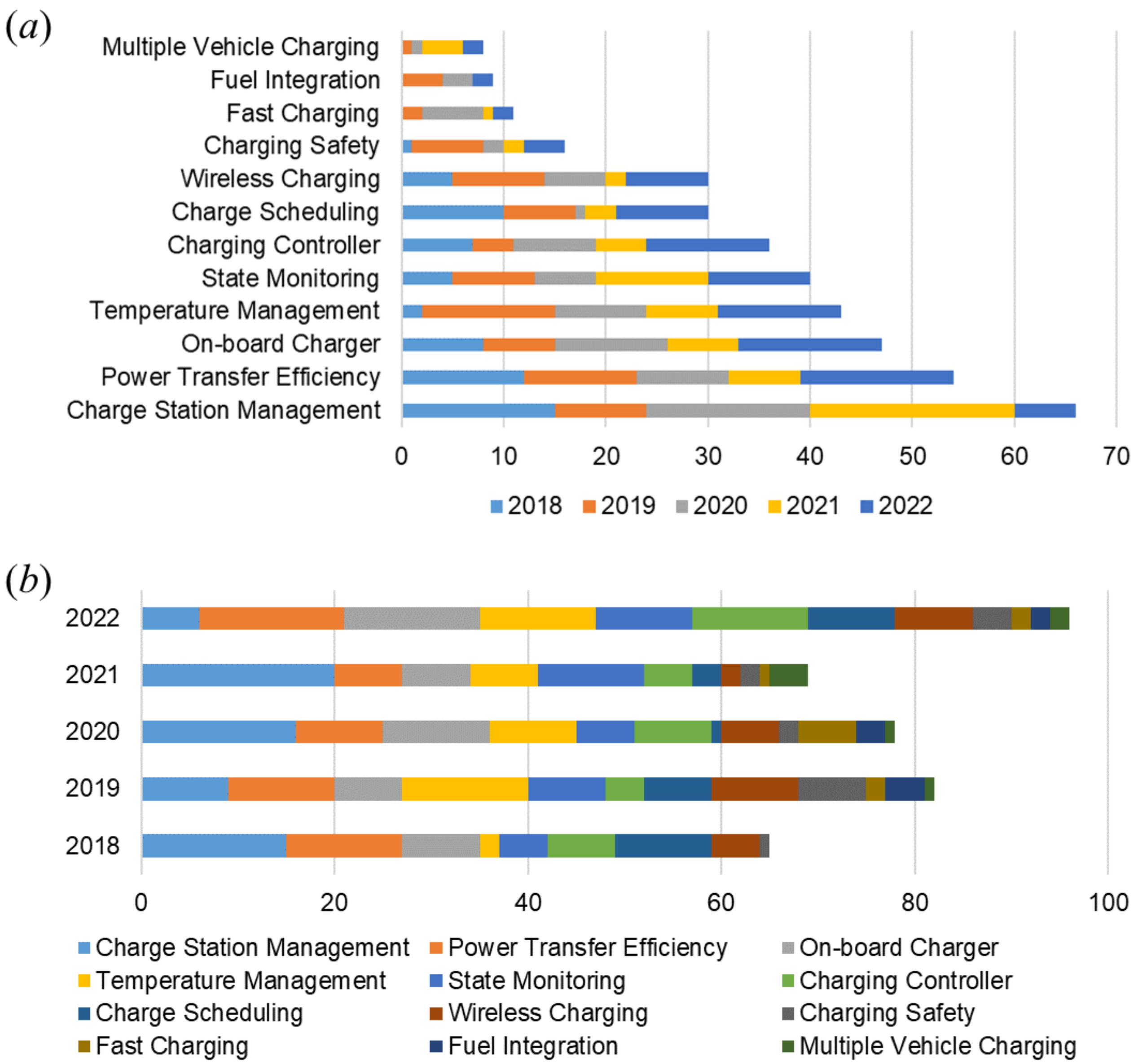

Figure 5. Distribution of (**a**) theme by year and (**b**) year by theme.

The top invention theme of charge station management broadly addressed issues related to the availability, accessibility, and capacity of charge stations. This result mirrors the literature review findings that the shortage of charge station availability is a key factor currently affecting EV adoption. The next dominant themes of power transfer efficiency and on-board chargers reflect the expectation that manufacturers are seeking ways to reduce power loss while minimizing the cost and size of charger units for either fixed stations or on-board charger systems. The next two dominant themes of temperature management and state monitoring reflect current concerns about the dangers of overheating batteries and the need to reliably monitor the operating state of chargers and batteries. Each of the themes in wireless charging, fast charging, and charging multiple vehicles (such as fleets) accounted for less than 10% of the patents issued. This suggests that the industry is still at the frontier of addressing those problems.

4.3. Theme Relationships

To evaluate how documents clustered among the themes, the heatmap of Figure 6 provides a color-coded representation of how the cosine similarity vectors clustered. Each row of the heatmap represents a document cluster, and each column displays a color code for the mean cosine similarity value for the theme indicated by the column label. The k-means algorithm generated 10 clusters of documents and normalized the mean cosine similarity scores to the [−1, 1] range for visualization. The results indicate that each document cluster is associated mostly with a single theme. That is, only one theme has the brightest color (highest value) in each row. This result validated that the clustering algorithm successfully assigned a single best theme to each document.

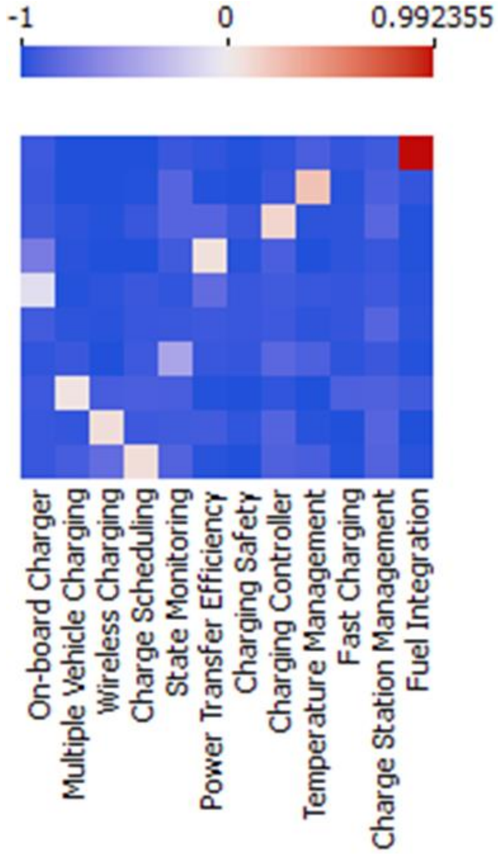

Figure 6. Document clustering.

Figure 7 shows the t-SNE results after projecting the cosine similarity vectors down to two dimensions. The results show that documents within a theme tend to be in the same neighborhood of the t-SNE feature space, as expected from the heatmap clustering results. Documents at the extreme corners of the feature space tended to have less overlap in their invention objectives than those closer to the center.

The opposite positioning of those documents toward extreme ends of the feature space suggested that they had minimal overlap in invention objectives. Hence, in most cases, the inventions tended to address those two problems as distinct from each other. This result is intuitively appealing because in most cases, the loss of power from inefficient conversion can release the wasted energy as heat. Therefore, improving power transfer efficiency can reduce heat generation as a byproduct, making it an unnecessary objective of the invention. However, temperature management can also refer to preventing the battery from overheating during charging. In such cases, those documents tended to be closer to documents with a "state monitoring" theme, which is also intuitively appealing. That is, a system must monitor the temperature of a battery to determine its optimal charging needs.

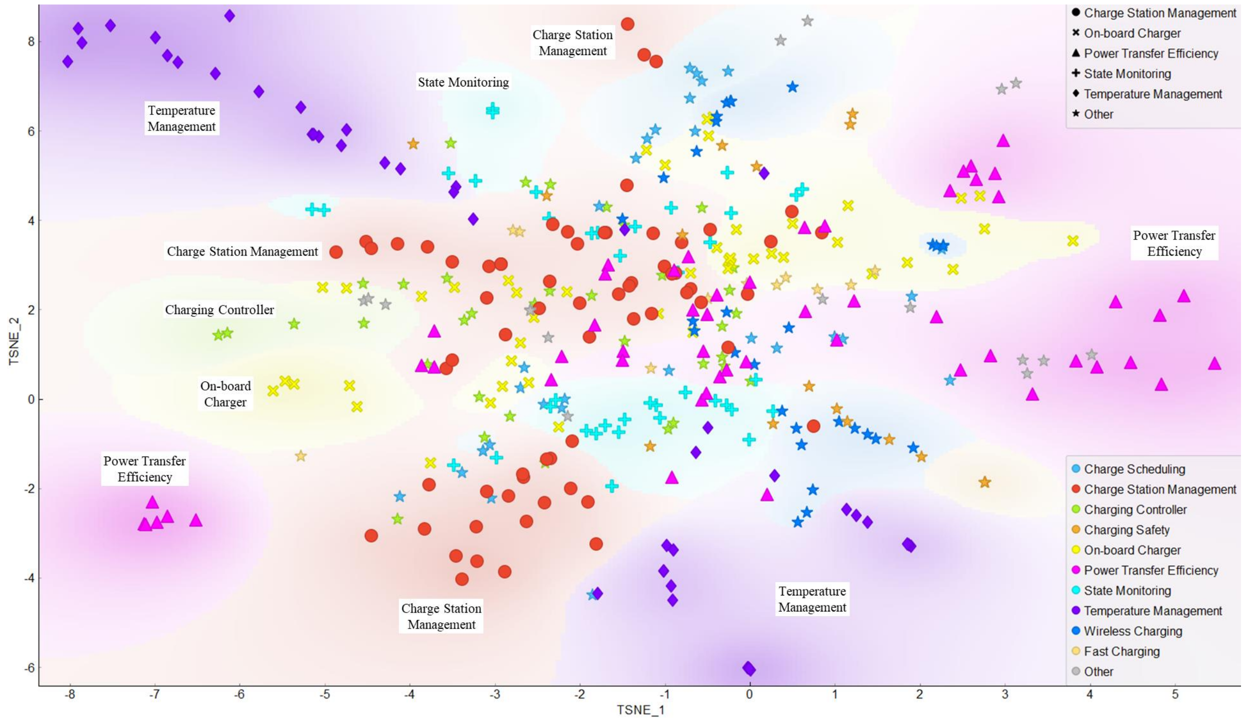

Figure 7. T-SNE manifold projection of topic similarities. For example, documents within the "temperature management" theme are split into clusters toward the upper left and lower right of the feature space, whereas documents within the "power transfer efficiency" theme are split into clusters toward the lower left and upper right of the feature space.

Documents clustering near the center of the feature space had more overlapping invention objectives than documents in homogeneous clusters toward the edges of the feature space. For example, a few documents within the "charge station management" theme appeared near clusters with themes like "state monitoring" and "on-board charger" near the center of the feature space. This suggested related invention objectives among those themes. In general, the t-SNE modeling of document relationships revealed that, as expected, even though the inventions focused on a single objective or theme, there was overlap with other themes.

4.4. Practical Implications

Insights gleaned from the findings of this research can significantly influence the trajectory of research, development, and policy formulation to spur the adoption of EVs. Given that more than half the patents focused on solutions relating to charging station management, power transfer efficiency, on-board charger design, and temperature management, industry stakeholders should consider focusing their R&D efforts in these domains for immediate impact. Patents focused on wireless and fast charging were in the minority, suggesting an untapped market potential with opportunities to pioneer and gain a competitive edge. Policymakers can allocate resources more efficiently to help accelerate the development and deployment of efficient and reliable EV charging systems by focusing on the core themes identified. Given the gaps in wireless and fast charging innovations, policymakers should consider providing incentives for R&D in these areas. Furthermore, policymakers should work toward harmonizing the existing standards to facilitate interoperability and widespread adoption. Researchers can adopt the text mining workflow developed in this study to analyze trends in other technology domains. The core themes and less-represented areas identified in this study can guide investments in companies that are likely to shape the future of EV charging technologies.

4.5. Limitations

There are three limitations to this study. First, patents alone do not reflect the full world knowledge about the development of a particular technology. Inventors do not necessarily disclose all innovations that their companies intend to commercialize, and not all inventions are patentable. The second limitation is that NLP methods operate primarily on the statistical distributions of phrases in a document, so they are not always helpful in identifying unique themes. A human expert must still examine the output and identify a unique theme based on the dominant keywords identified. In future work, the author will compare how much other NLP methods can help humans classify patent objectives. The third limitation is that the workflow is difficult to automate and scale to large datasets because a human must label a subset of the data.

5. Conclusions

The steady adoption of electric vehicles (EVs) is an essential step toward achieving global decarbonization goals and environmental sustainability. However, the development and deployment of efficient, dependable, and cost-effective EV chargers remains a significant challenge. This study employed a unique text mining workflow, combining natural language processing (NLP) and machine learning (ML) techniques, to analyze U.S. patent award summaries and identify key themes in EV charger technology and product development.

The analysis revealed a 47.7% increase in the number of EV charger patents issued in 2022 compared with that in 2018. The dominant themes were charging station management, power transfer efficiency, on-board charger design, and temperature management. These themes accounted for over half (53.8%) of the patents issued during the study period. Interestingly, less than 10% of the patents focused on wireless charging, fast charging, and fleet charging, indicating that these areas are still at the frontier of technological advancements.

These findings have implications in policymaking, investment decisions, industry focus, and academic research. Policymakers and investors can use these insights to allocate resources more effectively toward R&D in the EV charging sector. The study suggests that the industry is making significant strides in certain areas while others, such as wireless and fast charging, require more attention. This study fills a gap in the scholarly literature by providing a comprehensive overview of practical solutions and challenges in EV charger technology development, which can guide future academic research. Given the low percentage of patents in wireless charging and their potential to increase charging convenience, future research could focus on their technical and economic feasibility. With growing demand for fast charging, the industry needs solutions that can balance rapid charging with battery lifespan. As EV chargers become more interconnected, future work should also focus on cybersecurity measures to protect the charging infrastructure.

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