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Original Research

Data-driven decision analysis for weather observation technology in Japan: Integrating patent forecasting, network analytics, and economic valuation

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Abstract: Accurate weather observation is paramount for mitigating the severe impacts of natural disasters, particularly in geographically vulnerable countries like Japan. This study provides a data-driven analysis of recent patent trends in Japanese weather observation technology to identify high-potential areas for future investment. Given Japan's susceptibility to extreme weather, enhancing forecast accuracy is crucial for economic and social resilience. We analyzed 93 patents published from 2019 to 2023 using an integrated methodology that combines patent mining, ARIMA-based time series forecasting, and Social Network Analysis (SNA). This approach enables us to identify key technologies, forecast their growth trajectories, and map their structural importance within the innovation ecosystem. Our analysis reveals that "control" technology is the leading field for future development, characterized by a rapidly growing ("Hot") trend and high structural centrality in the technology network. To validate its commercial relevance, we conducted an economic valuation using the Expected Value of Perfect Information (EVPI) and the Expected Value of Sample Information (EVSI). The results demonstrate a quantifiable positive return on investment for developing advanced control systems, confirming their economic viability. This research offers a robust, multi-faceted framework for strategic decision-making, providing actionable insights for stakeholders by directly linking technological forecasting to economic valuation.

Keywords: Data-driven decision analysis, Weather observation technology, Patent forecasting, Network analytics, Economic valuation

1. Introduction

Japan’s unique geographical location and complex topography make it highly susceptible to a wide array of natural disasters, including typhoons, torrential rainfall, earthquakes, and other severe weather phenomena [1, 2]. These recurring events pose significant threats to human life, critical infrastructure, and national economic stability. Therefore, the development and enhancement of accurate weather forecasting and early warning systems are not merely scientific persuits but essential components of national security, public safety, and disaster risk management [3, 4]. In particular, the ability to deliver timely and precise forecasts directly affects the capacity of governments, industries, and communities to minimize damage and safeguard resilience in the face of environmental hazards. Meteorological observation technology is

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central to these forecasting and early warning systems. This technology generates the raw data that supports all subsequent models, predictions, and analytical outputs. The effectiveness of any observation system is therefore closely linked to its technological sophistication: higher-resolution sensors, advanced remote-sensing platforms, and integrated data networks contribute directly to greater predictive accuracy and shorter alert times. Continuous innovation is indispensable, as incremental improvements in observational capacity can yield exponential gains in forecasting reliability and disaster response effectiveness.

Patent analysis provides a particularly valuable perspective for understanding how such innovation evolves [5, 6]. Patents represent codified knowledge and intellectual property that often precede the commercialization of new products or services [7]. They also reflect the strategic priorities of both firms and research institutions, offering a window into emerging technological trajectories [8]. By systematically examining patent applications, researchers can identify nascent areas of innovation, monitor the pace of technological development, and anticipate which domains are most likely to generate impactful advances. In the context of weather observation, patents reveal not only technological progress in instrumentation and data processing but also innovations in satellite systems, IoT-enabled sensors, and AI-driven analytical tools. Against this backdrop, the present study conducts a comprehensive analysis of patent application trends in weather observation technology in Japan. To be clear, this study does not develop a new meteorological forecasting method itself, nor does it predict the weather. Instead, its primary contribution is the creation and application of a novel, integrated framework for technology forecasting. The objectives of this research are threefold: (1) to identify the most promising technological trajectories within weather observation patents, (2) to evaluate the commercial potential of these technologies, and (3) to provide actionable insights for stakeholders. By integrating patent forecasting, network analytics, and economic valuation, this study develops a data-driven roadmap to guide strategic R&D investment in Japan's weather observation technologies.

The broader significance of this research lies in its ability to inform decision-making across multiple sectors. For technology firms, it highlights high-potential areas for R&D investment [8]. For policymakers, it offers evidence-based guidance for resource allocation and strategic foresight [5, 6]. For researchers, it helps align research agendas with pressing technological needs and emerging industrial applications [9]. The proposed methodology provides a replicable framework for assessing technological trends and their economic viability, which is a critical need in high-stakes fields such as disaster management [3, 4].

This is particularly relevant for Japan, whose weather observation infrastructure is among the most advanced in the world. The Automated Meteorological Data Acquisition System (AMeDAS), illustrated in Figure 1, exemplifies this with its dense nationwide network. The map in Figure 1 shows hundreds of observation sites, including

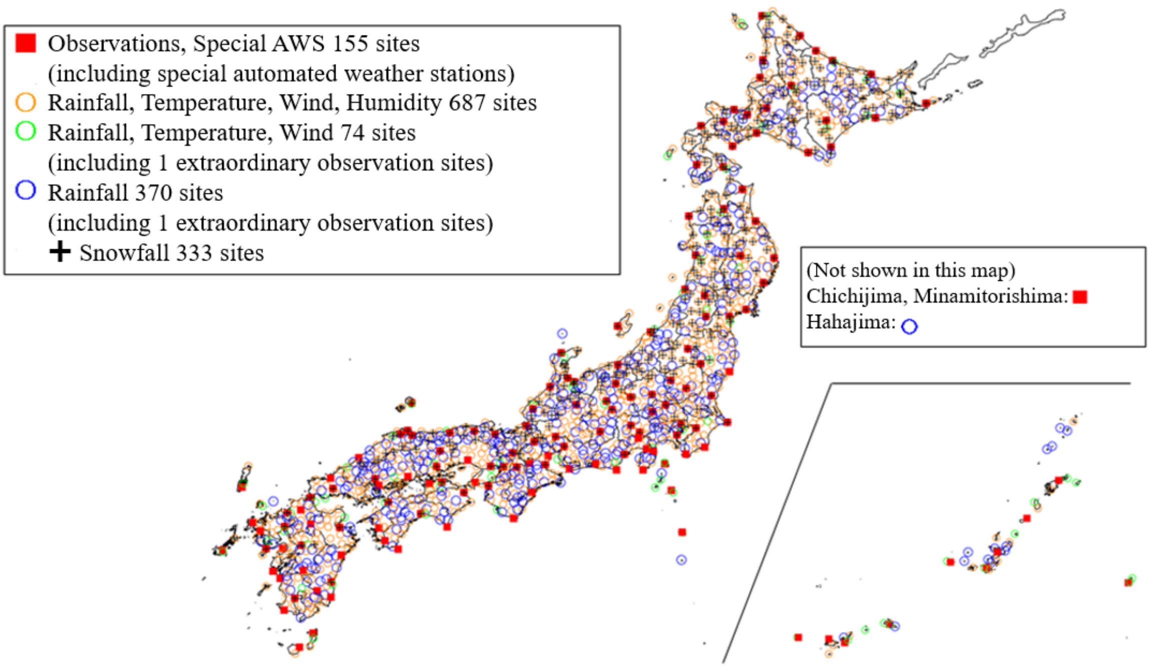


Figure 1. Nationwide coverage of Japan's AMeDAS weather observation network

specialized stations for rainfall, temperature, wind, and snowfall, forming a comprehensive data collection backbone. Although AMeDAS has been instrumental, the increasing demands driven by climate change necessitate continuous innovation [10]. Understanding the evolution of technologies that can enhance or supplement such systems is critical for maintaining Japan's leadership in meteorological prediction and disaster resilience.

2. Literature review

2.1 Weather observation technology in Japan

Japan's weather observation capabilities are among the most advanced globally, orchestrated primarily by the Japan Meteorological Agency (JMA) [11, 12]. The backbone of this observation network is the AMeDAS network, which comprises approximately 1,300 automated stations distributed across the country [10, 13]. These stations provide continuous, real-time data on precipitation, temperature, wind, and other critical meteorological variables. This dense observational infrastructure is further supported by a wide range of complementary technologies, including weather radars, geostationary satellites such as the Himawari series, radiosondes, and wind profilers [14, 15]. Together, these technologies produce a comprehensive and high-resolution dataset that serves as the foundation for advanced numerical weather prediction models. Such models are indispensable in a country like Japan, where mountainous terrain and exposure to extreme weather events and highly localized and accurate forecasts are demanded.

Recent technological advancements have focused on improving both data quality and predictive power. Innovations include phased-array radars for faster precipitation monitoring and the integration of artificial intelligence (AI) into data processing. AI-driven techniques such as machine learning are refining pattern recognition and improving short-term forecasts, making a paradigm shift toward data-centric meteorology [16]. This evolution represents a convergence of traditional atmospheric science with computational intelligence. Figure 2 provides a synthesized view of this multi-modal approach, illustrating how various technologies—from ground-based radar and observation posts to satellite-based sensors (GSM) and atmospheric tools like radiosondes—work in concert [17]. This integrated system combines physical models with advanced analytics to achieve higher levels of forecasting reliability [18].

2.2 Patent analysis in technology forecasting

Patent analysis has long been recognized as a systematic approach for anticipating technological change and assessing innovation potential [19]. Because patents represent legally protected intellectual property and codified knowledge [20], they often indicate technological directions well before new products or services reach the market [21]. Analyzing patent data thus provides valuable foresight into emerging domains and the likely trajectory of innovation [9].

A range of analytical techniques has proven effective in extracting strategic intelligence from patent data [22]. For example, Huang and Li [5] used patent citation networks to analyze technology life cycles, demonstrating the value of longitudinal analysis. Similarly, text mining methods such as Term Frequency–Inverse Document Frequency (TF-IDF) have been widely applied to identify core technical concepts within patent corpora [23, 24]. For forecasting, Kwon and Jun [9] utilized the Autoregressive Integrated Moving Average (ARIMA) model to predict logistics technology trends based on patent filing dynamics. However, while these studies effectively apply individual methods, a significant research gap remains in integrating these disparate techniques into a single, cohesive framework. Few studies combine time-series forecasting, network-based structural analysis, and economic valuation to provide a holistic, decision-oriented assessment of a technology domain.

Table 1 summarizes representative studies in this area and highlights how the present research extends prior work. As shown, previous studies have mainly focused on isolated methodological perspectives—such as life cycle analysis, temporal trend forecasting, or structural mapping—without establishing an integrative workflow that links technological evolution to economic value. In contrast, our study synthesizes TF-IDF, ARIMA, Social Network Analysis (SNA), and economic valuation (EVPI/EVSI) within a unified analytical framework, offering more actionable insights for strategic decision-making in the context of weather observation technology.

In addition, network-based approaches enrich the analysis by uncovering the structural characteristics of technological ecosystems. Social Network Analysis (SNA) can be applied to patent co-classifications, citations, or co-inventorship to map the interconnections between technologies, institutions, and research communities [24]. Centrality measures derived from SNA highlight influential technologies that act as hubs or bridges, revealing not only which domains drive innovation but also how different technologies converge to form integrative platforms [25]. Such analyses are essential for identifying foundational technologies that may serve as enablers for multiple application areas, particularly in cross-disciplinary domains such as meteorology, where sensing, data processing, and artificial intelligence converge.

2.3 Economic valuation of information

In the context of R&D investment, decision-making is often conducted under substantial uncertainty regarding both technological feasibility and market adoption. Decision analysis provides rigorous tools to evaluate the economic value of reducing such uncertainty, with the Expected Value of Perfect Information (EVPI) and the Expected Value of Sample Information (EVSI) being two cornerstone methodologies [26]. EVPI represents the theoretical maximum value that decision-makers would be willing to pay to eliminate all uncertainty about future states of the world [27]. It quantifies the difference between expected payoffs under perfect knowledge and those under current, imperfect knowledge. While perfect information is rarely attainable, EVPI serves as an upper bound that indicates the potential value of investing in additional information-gathering activities such as advanced R&D, large-scale field experiments, or comprehensive data acquisition [28].

EVSI, by contrast, provides a more practical measure of the expected benefit of acquiring additional but imperfect information. Examples include targeted pilot studies, prototype testing, or partial datasets that reduce, but do not eliminate, uncertainty. When the EVSI of an activity exceeds its cost, the investment is considered economically justifiable [29]. This criterion makes EVSI particularly valuable for research prioritization, as it balances the cost of inquiry with the incremental decision-making benefits gained from improved knowledge [30]. In recent years, EVPI and EVSI have been applied in fields ranging from healthcare technology assessment to energy systems planning, demonstrating their versatility as tools for strategic decision-making [31, 32]. Applying these frameworks to patent analysis enables the translation of technological signals—such as emerging trends in meteorological observation patents—into quantifiable economic terms. This, in turn, enables firms, policymakers, and funding agencies to make more informed choices about R&D investments, ensuring that resources are directed toward technologies with the greatest potential to enhance predictive accuracy, resilience, and societal benefit.

3. Methodology

3.1 Data collection

This study employs a multi-stage research methodology to identify promising technologies in the field of weather observation and to evaluate their economic potential using patent data. As the first step, the dataset focuses on patents related to weather observation technology filed in Japan between January 1, 2019 and December 31, 2023, ensuring coverage of the most recent technological trends. Patent data were retrieved from the Japan Patent Office (JPO) database via the Google Patent search interface [33], which provides access to the JPO's patent repository [34]. English language settings were used to maintain consistency and accessibility. The search employed the following keywords: "weather observation system," "weather prediction model," "atmospheric exploration technology," "weather observation," and "weather prediction." This process yielded a final dataset of 93 relevant patents, which serve as the basis for subsequent analyses. The detailed parameters of the data collection process are summarized in Table 2.

3.2 Data analysis

The data analysis phase of this study employed a comprehensive and multi-layered framework integrating keyword extraction, time series forecasting, social network analysis (SNA), and economic valuation. This approach ensures that the study not only identifies emerging technologies but also evaluates their potential value in a rapidly evolving innovation ecosystem. Each analytical step builds upon the previous one, allowing for a systematic progression from the extraction of technical knowledge to its prioritization based on both temporal and structural indicators, ultimately linking technological potential to

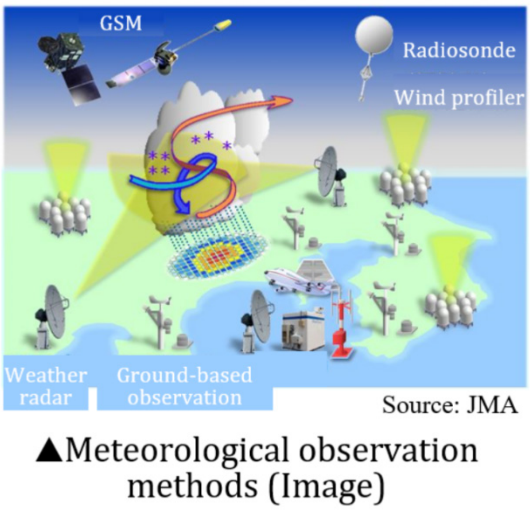


Figure 2. Overview of Japan’s multi-modal meteorological observation system

Table 1. Comparison of methodological approaches in technology forecasting

Study	Methodology used	Focus area	Limitation / gap addressed by our study
Huang, Li [5]	Patent citation networks	General technology life cycles	Focuses on life cycle analysis but lacks keyword-level trend forecasting and economic valuation.
Kwon, Jun [9]	ARIMA time series	Logistics technology	Provides temporal forecasting but does not analyze the structural importance of technologies (via SNA) or their economic value.
Jee, Shin [24]	Multiple patent analysis approaches (including SNA)	General promising technology identification	Compares different methods but does not integrate them into a single workflow or link findings to economic decision-making (EVPI/EVSI).
This Study	Integrated framework (TF-IDF, ARIMA, SNA, EVPI/EVSI)	Weather observation technology	Synthesize temporal forecasting, structural network analysis, and economic valuation to provide actionable, prioritized insights.

Table 2. Detailed information about the selected patent data

Data collection parameters	Information
Research Keywords used in the Search	"weather observation system", "weather prediction model", "atmospheric exploration technology", "weather observation", "weather prediction"
Period	2019~2023 (Publication Year, Last 10 Years)
Database	Japan Patent Office (Google Patent, English)

economic decision-making.

3.2.1 Keyword extraction and analysis

The first step in our analytical framework involved the identification of key technical concepts embedded within the patent corpus. Patent documents particularly abstracts and claims were subjected to text mining techniques to extract technical terms that accurately represent the innovations described. To assess the significance of these terms, we employed the Term Frequency–Inverse Document Frequency (TF-IDF) metric, as expressed in Equation 1 [35].

$$\text{TF-IDF}(t,d,D) = \text{TF}(t,d) \times \text{IDF}(t,D) \quad (1)$$

$$\text{IDF}(t,D) = \log\left(\frac{|D|}{|\{d \in D: t \in d\}|}\right) \quad (2)$$

Here, TF(t,d) represents the frequency of term t in document d, while Equation 2 measures the rarity of term t across the entire document set D. Terms that frequently appear in a single document but are uncommon across the corpus are considered highly informative. The application of TF-IDF enabled us to isolate core technological concepts. To ensure the quality of the extracted keywords and enhance the robustness of the analysis, a filtering process was applied. This involved removing common English stop-words and filtering out terms with a document frequency below a set threshold (i.e., appearing in fewer than three patents) to eliminate idiosyncratic noise and focus on more prevalent technologies. By focusing on statistically significant and domain-relevant keywords rather than generic terms, we ensured that subsequent analyses were built upon a robust and conceptually meaningful technical foundation.

3.2.2 Time series analysis

Once the critical keywords were identified, we investigated their temporal dynamics to uncover patterns of technological evolution. The annual frequency of patents associated with each keyword was analyzed to detect growth trajectories over the study period (2019-2023). This approach enabled us to distinguish between technologies that are emerging, stable, or in decline. To forecast future trends, we employed the Autoregressive Integrated Moving Average (ARIMA) model, as specified in Equation 3 [36].

$$\phi(B)(1-B)^d Xt = \theta(B)\varepsilon t \quad (3)$$

In this expression, $\phi(B)$ denotes the autoregressive polynomial of order p, $(1-B)^d$ represents differencing of order d to remove non-stationarity, $\theta(B)$ is the moving average polynomial of order q, and ε_t is white noise. The ARIMA model was selected due to its proven effectiveness and interpretability in analyzing univariate time-series data, particularly in patent forecasting where temporal dependencies and trend persistence are prevalent [9]. Its ability to handle non-stationary data through differencing makes it well-suited to real-world datasets such as patent filing frequencies, which often lack a stable mean or variance.

The selection of the optimal ARIMA(p, d, q) order for each keyword series was performed systematically. First, the degree of differencing (d) was determined using the Augmented Dickey–Fuller (ADF) test to ensure stationarity. Next, the autoregressive (p) and moving average (q) orders were identified by examining the Autocorrelation (ACF) and Partial Autocorrelation (PACF) plots of the differenced series. Final model selection was guided by the principle of parsimony, minimizing the Akaike Information Criterion (AIC) to prevent overfitting while maintaining predictive power. Although alternative models such as exponential smoothing, Prophet, or deep learning approaches (e.g., LSTMs) could be considered, ARIMA was selected for its interpretability, suitability for small-sample series, and well-established methodological rigor in the context of technological forecasting.

The application of the ARIMA model enabled the classification of technologies into three distinct categories based on their temporal patterns. Hot technologies exhibited rapidly increasing trends, signaling emerging areas with strong innovation potential. Active technologies demonstrated steady upward trajectories, indicative of sustained research interest and ongoing market relevance. Conversely, cold technologies displayed flat or declining patterns, suggesting they are either mature fields with limited advancement potential or areas experiencing declining competitive importance within the innovation landscape.

3.2.3 Social network analysis (SNA)

Technological progress rarely occurs in isolation; innovations are interconnected through shared concepts and applications. To capture this relational dimension, we constructed a co-occurrence network of keywords, where nodes represent technical terms and edges signify their joint presence within patent documents. This network-based perspective provides insight into how technologies interact and which concepts serve as central hubs in the innovation ecosystem [37]. Two key centrality measures were calculated to assess the importance of each keyword: Degree Centrality in Equation 4 and Betweenness Centrality in Equation 5 [38]. By evaluating these centrality metrics, we assigned priority levels (High, Medium, Low) to each keyword, enabling us to differentiate between core enabling technologies and peripheral developments.

$$C_D(i) = \frac{d(i)}{n-1} \quad (4)$$

$$C_B(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \quad (5)$$

3.2.4 Economic valuation of technology

While technological relevance is essential, its economic viability ultimately determines whether a technology will be pursued in practice. To assess this, we integrated decision-analytic methods [39], specifically the Expected Value of Perfect Information (EVPI in Equation 6) and Expected Value of Sample Information (EVSI in Equation 7) [40]. By comparing EVPI and EVSI, we can determine whether investing in further research is justified given the potential returns, thus providing a quantitative basis for R&D prioritization.

$$\mathrm{EVPI} = E_\theta\left[\max_a V(a,\theta)\right] - \max_a E_\theta[V(a,\theta)]$$

(6)

$$\mathrm{EVSI} = E_X\left[\max_a E_{\theta|X}[V(a,\theta)]\right] - \max_a E_\theta[V(a,\theta)]$$

(7)

3.2.5 Integrated analysis framework

The final step of our analysis synthesizes the temporal insights from the ARIMA forecasts with the structural insights from the network analysis. This integrated framework enables the identification of technologies that are both rapidly emerging and structurally central to the innovation landscape. Such technologies are prime candidates for strategic investment, as they not only demonstrate growth potential but also occupy pivotal positions within the broader technological ecosystem. This comprehensive approach moves beyond static assessments, providing actionable intelligence for policymakers, investors, and researchers seeking to foster innovation in weather observation technologies.

4. Results

4.1 Patent application trends

The annual frequency of patent applications related to weather observation technology from 2019 to 2023 is shown in Figure 3. The data indicates a peak in 2019, followed by a dip in 2020, and a subsequent recovery and stabilization in the following years. The top 10 patent applicants are listed in Table 3. Notably, the list is led by automotive and electronics giants, with Honda Motor Co., Ltd. (7 patents), Denso Corporation (6 patents), and Mitsubishi Electric (5 patents) as the top three. These top 10 applicants account for nearly 40% of the patents in the dataset, indicating a significant concentration of R&D in this sector among major industrial players.

4.2 Keyword analysis

From the 93 patents, 193 distinct technical keywords were extracted and analyzed. The descriptive statistics of their TF-IDF scores are presented in Table 4. The top 10 most important keywords, ranked by their TF-IDF scores, are shown in Table 5. "Process" and "manag" (management) achieved the highest scores, appearing in 31.2% and 33.3% of patents, respectively. Other highly ranked keywords include "system," "control," "vehicl" (vehicle), and "informat" (information), highlighting a focus on data processing, system control, and mobile observation platforms. The keyword "informat" was the most frequent, appearing in over half of the analyzed patents (54.8%).

4.3 Time series analysis

The ARIMA model was applied to forecast trends for the key technical terms, enabling their classification into "Hot," "Active," or "Cold" fields, as illustrated in Figure 4. The results, summarized in Table 5 (Result of Time Series Analysis), reveal distinct developmental trajectories across different technological areas. Hot Fields include the terms "method," "system," "devic," "program," and "control." These keywords exhibit a rapidly increasing trend, indicating that innovation is accelerating in areas such as new technological methods, integrated systems, physical devices, software development, and automated control logic. The steep upward trajectory of these terms suggests

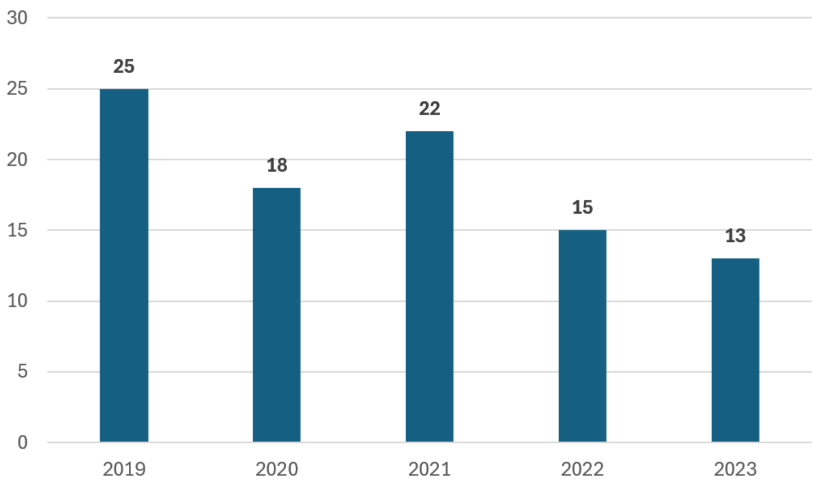


Figure 3. Frequency of patents applications

Table 3. Top 10 patent applicants

Rank	Applicant	Number of patents filed (patent share)
1	Honda Motor Co., Ltd.	7 (7.5%)
2	Denso Corporation	6 (6.4%)
3	Mitsubishi Electric	5 (5.3%)
4	RICOH	3 (3.2%)
5	NEC Corporation	3 (3.2%)
6	Soft Bank Corporation	3 (3.2%)
7	Toyota Motor Corporation	3 (3.2%)
8	Riken Technos Corporation	3 (3.2%)
9	Toshiba Corporation	2 (2.1%)
10	Hitachi Astemo, Ltd.	2 (2.1%)
Sum		37 (39.8%)

Table 4. Descriptive statistics of identified technical keywords

Descriptive statistics	TF-IDF score
N	193
Max	10.5718
Q3	2.17972
Median	1.367036
Q1	1.039045
Min	0.272465

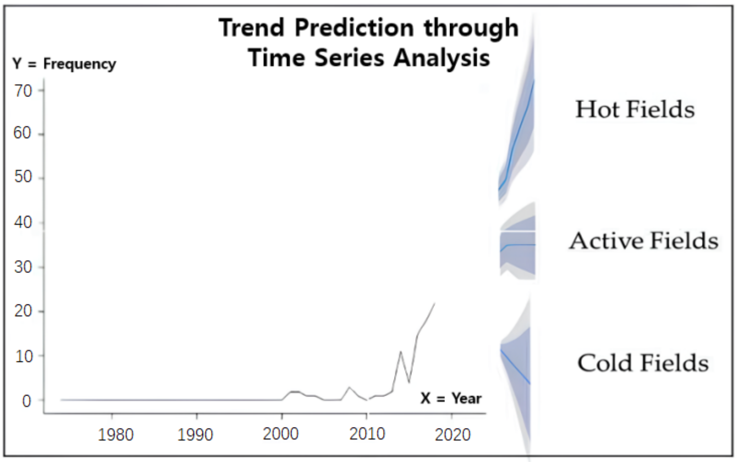


Figure 4. Example of Time Series Analysis

Table 5. Result of time series analysis

Technical keyword	Fields
method, system, devic, program, control	Hot
manag, process, inform, informat	Active
vehicl	Cold

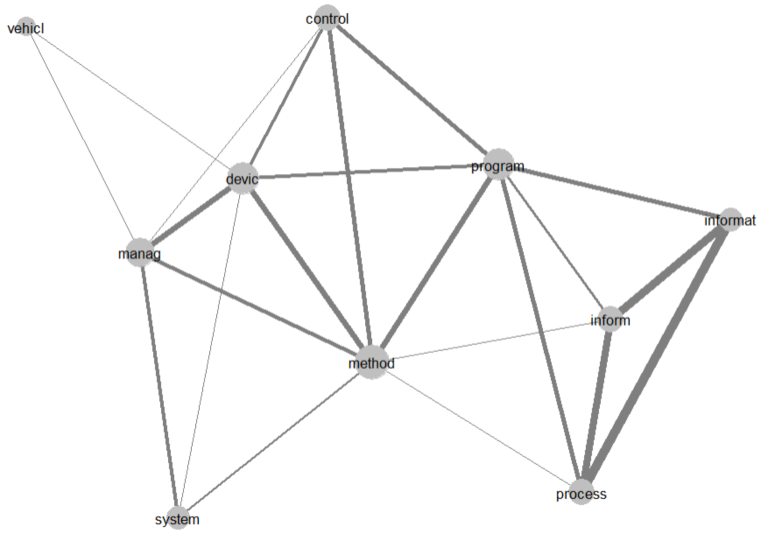


Figure 5. Results of social network analysis visualization

strong and growing research focus, highlighting them as emerging priorities for R&D investment.

Active Fields encompass the terms "manag," "process," "inform," and "informat." These keywords show steady, positive growth, reflecting sustained efforts in data management, processing workflows, and information system development. The consistent upward trend indicates ongoing interest and incremental technological advancement rather than sudden emergence, marking them as stable areas of innovation. Cold Fields are represented by the keyword "vehicl." Although vehicle-based data collection remains relevant, as evidenced by the applicants listed in Table 3, its growth trajectory is comparatively flat. This classification suggests that while the field continues to contribute to the broader technological landscape, its role as a distinct driver of innovation may be slowing relative to other emerging and active areas.

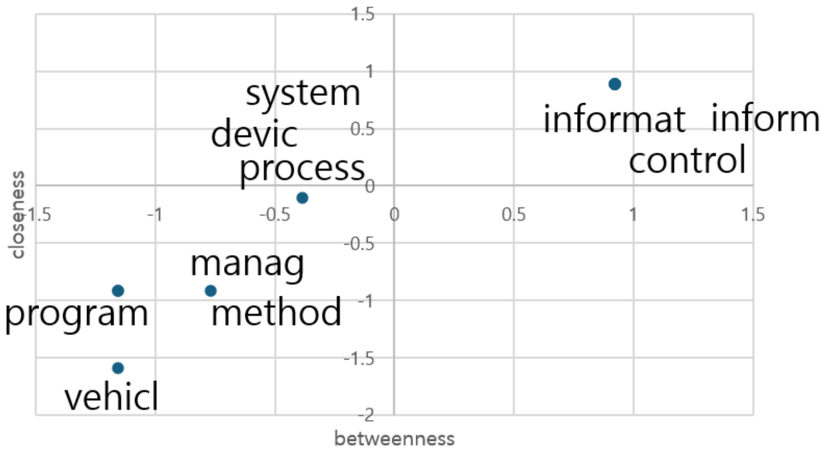
4.4 Social network analysis

To understand the relationships between technologies, a co-occurrence network was created, as visualized in Figure 5. In this network, each node represents a technical keyword, and an edge (line) connecting two nodes signifies that they appeared together in the same patent. The thickness of the edge is proportional to their co-occurrence frequency; a thicker line, such as that between "control" and "system" indicates a stronger technological relationship. Central keywords can be visually identified by their numerous and thick connections, suggesting that they are integral components of the innovation ecosystem and serve as critical points of technological convergence.

To quantify this visual intuition, we calculated centrality metrics for each keyword, as illustrated in Figure 6 and summarized in Table 6. The x-axis represents Betweenness Centrality, which measures how often a keyword acts as a "bridge" on the shortest path between two other keywords.

A higher score indicates that the keyword plays a connecting role across otherwise separate technological clusters. The y-axis represents Closeness Centrality, which measures how easily a keyword can connect to all other keywords in the network, reflecting its capacity to efficiently disseminate or gather technological information.

This two-dimensional mapping functions as a technology priority map. Keywords located in the upper-right quadrant—exhibiting both high betweenness and high closeness centrality—are considered high-priority because they serve as both critical bridges and efficient hubs in the technology network. As shown in Table 6, "control", "inform", and "informat" fall into this



	Average	SD
betweenness	**1**	**0.86638172**
closeness	**0.101161616**	**0.011202689**

Figure 6. Technology mapping results each technical keywords based on centrality

Table 6. Result of social network analysis

Technical Keyword	Priority
control, inform, informat	High
-	Medium
method, system, devic, program, manag, process, vehicl	Low

category, underscoring their central and integrative roles in the innovation structure. In contrast, keywords such as "method", "system", "device", "program", "manage", "process" and "vehicle" exhibit lower centrality values and are classified as low-priority. These terms represent more specialized or peripheral technologies that, while relevant, exert less structural influence on the overall technological landscape.

4.5 Integrated analysis

By synthesizing the findings from the time series analysis (TSA) and social network analysis (SNA), we developed an overall priority ranking for the technology fields, as summarized in Table 7. This integrated framework highlights technologies that are both structurally central within the innovation network and exhibit strong growth momentum over time, ensuring that emerging trends and key integrative technologies are considered simultaneously for strategic prioritization.

Priority 1 is assigned to "control", which emerged as the top-ranked technology. It is classified as a "Hot" field in the time series analysis and possesses "High" centrality in the network, marking it as both rapidly growing and structurally pivotal. Priority 2 includes "inform" and "informat," which combine "High" network centrality with an "Active" growth trend, indicating that these technologies play a central role in knowledge integration while demonstrating moderate innovation momentum. Priority 3 consists of "method," "system," "devic," and "program." Although these keywords have "Low" network centrality, their "Hot" growth trend highlights them as significant areas of emerging technology.

Priority 4 encompasses "manag" and "process," representing established, active fields with steady growth, but lower structural importance in the network, suggesting they serve more as supporting technologies than as central hubs. Finally, Priority 5 is assigned to "vehicl", classified as both a "Cold" field and as having "Low" network centrality, reflecting limited growth and peripheral influence within the technological landscape. Overall, the integrated results strongly indicate that control technology is the most strategic and promising area for future R&D investment in Japanese weather observation, indicating that research resources should be concentrated in this field to maximize innovation impact.

4.6 Economic valuation

To translate our findings into a tangible business case, we conducted an economic valuation of the top-ranked technology, "control". We modeled a scenario in which an event organizer must decide whether to proceed with or cancel an event based on a weather forecast. The detailed calculations are presented in the spreadsheet shown in Table 9, which includes the payoff matrix, prior probabilities of weather states, and the conditional probabilities of forecast accuracy summarized in Table 8.

Table 7. Results of the integrated analysis frameworks

Technical keyword	Social network analysis	Time series analysis	priority
control	High	Hot	1
inform, informat	High	Active	2
method, system, devic, program	Low	Hot	3
manag, process	Low	Active	4
vehicl	Low	Cold	5

Table 8. Results of the integrated analysis frameworks

	Rain	Cloud	Clear
Rain (Actual Weather)	0.7	0.2	0.1
Cloud (Actual Weather)	0.3	0.5	0.2
Clear (Actual Weather)	0.1	0.3	0.6

Table 9. Result of scenario analysis using EVPI and EVSI

Category	Item / state	Rain	Cloud	Clear	Formula or probability	Remarks
1. Baseline Decision	Event progress payoff	-1500	-600	4000	—	—
	Event cancellation payoff	-200	-200	200	—	—
	Prior probability	0.7	0.2	0.1	—	ΣP = 1.0
	Expected Monetary Value (EMV)	—	—	—	EMV = Max(-770, -160) = -160	Optimal: Cancel
2. Perfect Information Scenario	Event progress payoff	-1500	-600	4000	—	—
	Event cancellation payoff	-200	-200	200	—	—
	Optimal choice payoff by state	-200	-200	4000	Max(Proceed, Cancel)	—
	Expected Value with Perfect Information (EVwPI)	—	—	—	(-200×0.7) + (-200×0.2) + (4000×0.1) = 220	—
	Expected Value of Perfect Information (EVPI)	—	—	—	EVwPI − EMV = 220 − (−160) = 380	Max potential value
3. Sample Information Scenario	Forecast accuracy (conditional probability) P(F │ S)	0.7 / 0.2 / 0.1	0.3 / 0.5 / 0.2	0.1 / 0.3 / 0.6	From Table 8	—
	Marginal Probability P(F)	0.56	0.27	0.17	P(F) = Σ[P(F │ S)P(S)]	—
	Posterior probability P(S │ F)	0.875 / 0.1071 / 0.0179	0.5185 / 0.3704 / 0.1111	0.4118 / 0.2353 / 0.3529	Bayes' theorem	—
	Optimal choice payoff (forecast-based)	-192.84 (Cancel)	-155.56 (Cancel)	652.72 (Proceed)	EMV(Proceed) vs EMV(Cancel)	—
	Expected Value with Sample Information (EVwSI)	—	—	—	Σ(Optimal Payoff × P(F)) = -39.00	—
4. Valuation Summary	Baseline EMV	—	—	—	-160	—
	EV with Sample Information (EVwSI)	—	—	—	-39.00	—
	EVSI = EVwSI − EMV	—	—	—	-39.00 − (−160) = 121.00	Positive value
	EVPI (Max potential value)	—	—	—	380	—

The analysis begins with the baseline decision. Without any additional information, the optimal choice is to cancel the event, yielding an Expected Monetary Value (EMV) of −160. This baseline provides a benchmark for evaluating the value of acquiring further information. The Expected Value of Perfect Information (EVPI) is 380, representing the maximum theoretical benefit of eliminating all uncertainty about the weather. We then modeled the Expected Value with Sample Information (EVSI) based on an improved forecast reflecting the potential benefit of investing in advanced control technology. The expected value under this scenario is −39, yielding an EVSI of 121 (−39 − (−160)). This positive EVSI demonstrates that even imperfect but enhanced information generates a net economic gain, providing quantitative justification for investing in superior control technologies and highlighting their strategic importance.

5. Discussion

5.1 Summary of findings

This study leveraged a multi-method framework to analyze 93 Japanese patents in weather observation from 2019 to 2023. The key findings are threefold. First, the R&D landscape is dominated by major automotive and electronics firms such as Honda and Denso. Second, our integrated analysis, which combined time series forecasting with network centrality metrics, clearly identified "control" technology as the highest-priority field. This conclusion is supported by robust evidence: "control" is not only a "Hot" field with a rapidly growing number of patents, but also a structurally critical hub in the innovation network, as demonstrated by its high betweenness and closeness centrality. Finally, our economic evaluation confirmed this strategic priority. By modeling a real-world decision scenario, we showed that investing in improved "control" systems yields a positive Expected Value of Sample Information (EVSI), providing a quantitative justification for R&D expenditure in this area.

5.2 Theoretical and practical implications

This research contributes to the field of technology forecasting by presenting a robust, integrated methodology that synthesizes insights from text mining, time series analysis, social network analysis, and economic valuation. This approach provides a more comprehensive and defensible assessment of technological trends than any single method alone. In particular, the inclusion of EVPI and EVSI bridges the gap between identifying technological trends and evaluating their economic viability, offering a direct link to strategic business decision-making. The framework highlights how combining statistical and modeling techniques can inform optimal R&D investment decisions.

The findings offer clear, actionable intelligence for companies. Technology firms, particularly in the automotive and IoT sectors, should recognize the strategic importance of "control" technologies. The results indicate that future value lies not only in data collection but also in sophisticated control systems that process this data for real-time, automated decision support. Practical applications may include vehicle-to-everything (V2X) communication for hyperlocal weather alerts or advanced control systems for drone-based atmospheric observation.

For policymakers and researchers, the study provides guidance for prioritizing initiatives and research directions. Government agencies and funding bodies should consider supporting R&D in control systems for meteorological applications, as enhancing these capabilities can improve national disaster preparedness and strengthen technological competitiveness. For researchers, the convergence of control engineering, artificial intelligence, and meteorology presents a promising area for innovation. The relative decline of "vehicle" as a hot keyword suggests a shift from viewing vehicles as simple sensor platforms to fully integrated nodes within a larger intelligent control network.

5.3 Limitations and future research

This study is subject to several limitations, which also provide meaningful directions for future research. First, as the reviewer noted, the dataset of 93 patents over a five-year period is informative but relatively limited. The robustness of the conclusions would be strengthened by extending the temporal scope to capture longer-term technological cycles (e.g., 10–20 years). Furthermore, a comparative analysis with international patents, particularly those from the United States Patent and Trademark Office (USPTO) and the European Patent Office (EPO), would offer valuable context for assessing Japan’s competitive position within the global innovation landscape. Additionally, the analysis was confined to patents filed in Japan and based on English-language search terms, which may not fully reflect the linguistic and conceptual nuances of the original Japanese patent documents.

Second, while the network analysis (Section 4.4 and Table 6) effectively identified the structural centrality and priority of technological keywords, the results are limited by the representativeness of the selected dataset. Expanding the keyword set and incorporating emerging terms from recent patent filings or research publications could provide a more dynamic understanding of evolving technological linkages and priorities.

Third, as the reviewer rightly pointed out, the economic valuation was based on a single illustrative case—an event organization scenario—designed primarily to demonstrate the methodological applicability of the proposed framework. While this example was effective for conceptual illustration, its generalizability remains limited. Future research should enhance the universality of these findings by exploring a broader range of application contexts. For instance, one could model the economic value of improved "control" technology (identified as a high-priority keyword in Table 6) for optimizing energy grid load balancing during extreme weather conditions or for guiding precision agriculture operations. Conducting a sensitivity analysis on key model inputs—such as payoff values, prior probabilities, and R&D cost parameters—would further increase the robustness and policy relevance of the economic implications under varying market conditions.

Finally, incorporating additional data sources such as scientific publications, news articles, and corporate financial reports could enable triangulation with the patent-based findings, offering a more comprehensive view of the innovation ecosystem. Complementary qualitative case studies of leading patenting firms would also deepen understanding of firm-level innovation strategies and the institutional drivers behind the observed technological convergence patterns.

6. Conclusion

This study provided a comprehensive, data-driven analysis of the current technological frontier in Japanese weather observation. Our integrated methodology successfully synthesized patent forecasting, network analytics, and economic valuation to identify strategic R&D priorities. Our findings clearly indicated a strategic shift towards more intelligent, automated, and interconnected systems, with "control" technology at the center of this transformation. By integrating rigorous patent analytics with established economic valuation models, we not only identified this key trend but also quantified its potential value, offering a solid foundation for strategic decision-making. As Japan continues to grapple with the challenges of a changing climate and extreme weather, investing in the advanced control technologies identified in this research will be paramount to enhancing its forecasting capabilities, protecting its citizens, and securing its economic future.

Conflict of interests

No potential conflict of interest was reported by the author.

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Data availability

Data will be made available on request.

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