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Original Research Article

AI-Based Technology Scouting Process in High-Tech Industries for Reducing R&D Project Risks: A Qualitative Thematic Analysis

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Abstract

Rapid technological advancements and the increasing complexity of the business environment have posed numerous challenges for high-tech companies in monitoring and forecasting technological developments. In this context, the emergence of artificial intelligence (AI) has opened new horizons in intelligent technology scouting. This study aims to identify and analyze key themes and components in the AI-based technology scouting process within high-tech companies, with the goal of reducing R&D project risks. Through thematic analysis methodology, 70 scientific articles published between 2014 and 2024 were systematically analyzed. The analysis resulted in the identification of 11 main stages, 44 primary themes, and 132 sub-themes within the AI-based technology scouting process. These themes were organized into a comprehensive and integrated model that encompasses not only technical aspects but also organizational, managerial, and strategic dimensions. The proposed process model can serve as a framework for designing and implementing intelligent technology scouting systems in high-tech companies, helping to mitigate risks associated with technological decision-making.

Keywords: Artificial intelligence; High-tech companies; Machine learning; Natural language processing; R&D Project Risks; Technology scouting.

Nomenclature and Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
ETL	Extract, Transform, Load
IoT	Internet of Things
KPI	Key Performance Indicators
ML	Machine Learning
NLP	Natural Language Processing
OCR	Optical Character Recognition
R&D	Research and Development
SWOT	Strengths, Weaknesses, Opportunities, Threats
TI	Technology Intelligence
UI	User Interface

1. Introduction

In today's era, organizations face complex challenges in monitoring and forecasting technological changes due to rapid technological transformations. These rapid developments, particularly in areas such as AI, the Internet of Things, cloud computing, and blockchain, have created increasing complexity in the business environment [1]. High-tech companies, in particular, face additional pressure to maintain their competitive advantage through rapid identification and response to technological developments. These companies must continuously monitor the technological environment, identify emerging opportunities, and prepare themselves for future changes [2].

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The emergence and advancement of AI has opened new horizons for intelligent technology scouting. Advanced AI capabilities in natural language processing, deep learning, and big data analytics enable the analysis of vast amounts of scientific data, patents, and technical reports [3]. These capabilities can help companies identify technological trends more quickly and accurately, predict future developments, and make strategic decisions. Moreover, AI's ability for continuous learning and adaptation can identify complex and hidden patterns in technological developments that might remain undetected by human analysts [4].

As a systematic process, technology scouting plays a vital role in the success of high-tech companies by identifying, evaluating, and predicting technological advancements. This process includes collecting, analyzing, and interpreting information related to scientific and technical developments that could impact an organization's competitive position and performance [5]. Today, the massive volume of technological data, the rapid pace of change, and the increasing complexity of relationships between technologies necessitate a more intelligent and efficient approach to monitoring. For instance, millions of new patent documents are published annually, making manual analysis practically impossible [6]. AI, with its unique capabilities in processing large volumes of data, identifying hidden patterns, and predicting future trends, can address these challenges and assist organizations in making strategic decisions, properly defining R&D projects, and reducing investment risks in these projects.

Failure to monitor technological developments in a timely manner can create serious risks for high-tech companies. These risks can lead to loss of competitive position, investment in incorrect technological paths, and even complete business failure [7]. Furthermore, the inherent complexity and uncertainty in technological forecasting require a systematic approach to risk management in the technology scouting process. In this context, the use of AI can help reduce technology decision-making risks by increasing the reliability of predictions and more accurate identification of weak signals of change [8].

Additionally, the increasing complexity of innovation ecosystems and the growing convergence of technologies have doubled the importance of intelligent technology scouting. Today, significant innovations often occur at the intersection of different technological domains, and identifying these intersection points requires complex and multidimensional analyses [9]. In such conditions, the use of AI in technology scouting is not just an advantage but a strategic necessity for high-tech companies, especially in reducing the risk of their R&D projects.

Previous studies in this field have addressed various aspects of the topic. Some researchers like Mühlroth and Grottke [10] focused on AI's role in identifying emerging trends and technologies, presenting an AI-based data mining model that helps companies identify emerging topics and trends. Sen et al. [11] examined the readiness of established companies in mature industries for restructuring and reorganizing technology intelligence processes in alignment with digitalization. In the field of patent analysis and technology mapping, Wang et al. [12] provided a framework for integrated analysis of technological evolution trends and competitive status.

Despite the value of these studies, there is a significant gap in providing a comprehensive and integrated model for AI-based technology scouting. Most existing research has either focused solely on technical aspects or addressed only part of the process. Moreover, few studies have focused on identifying and deeply analyzing key components and themes in this process from the perspective of high-tech companies [13].

Accordingly, this research aims to identify and deeply analyze themes and key components in the AI-based technology scouting process in high-tech companies. The main innovation of this research lies in presenting a comprehensive and systematic framework that encompasses not only technical aspects but also organizational, managerial, and strategic dimensions of this process. Using thematic analysis also enables the identification and understanding of deeper layers of this phenomenon.

The findings of this research are applicable to a diverse range of stakeholders. Managers and decision-makers in high-tech companies can use the presented framework to design and implement intelligent technology scouting systems. Technology experts and consultants can utilize this framework to guide the technology scouting process in organizations. Researchers can also use the findings of this study as a foundation for developing quantitative and empirical models in future research.

Based on this, the main research question is: What are the key themes and components in the AI-based technology scouting process in high-tech companies, and how can these components be organized into a comprehensive and integrated framework to reduce R&D project risks?

2. Literature Review

2.1 Conceptualization of Technology Scouting

Technology scouting, a key process in technology management, encompasses the continuous and systematic monitoring of an organization's technological environment. This process includes collecting, analyzing, and interpreting information related to scientific and technical developments that could impact an organization's performance and competitive position. Mirshah Velayati and Nazarizadeh [14] conceptualize technology scouting as a systematic process for identifying, evaluating, and predicting technological developments with the aim of reducing uncertainty and decision-making risks.

Technology scouting becomes important as organizations operate in a dynamic environment with rapid technological changes. Kujawa and Paetzold [15] believe that there are multiple methods for empowering companies to exploit new technologies and gain competitive advantage, and technology scouting is one of the most important of these methods. Khamseh and Behroozi [16] showed in their study that most successful institutions in developed countries use technology scouting as a powerful tool to gain more information about their environment.

In reviewing the literature, numerous studies have addressed the importance and necessity of technology scouting. Kerr and Phaal [17] state that in technology-driven sectors, strategic planning requires relevant and timely information about new and emerging technologies. They have developed an 'information needs' pattern to support the extraction and expression of meaningful search queries. Gonçalves and de Almeida [18] demonstrated through a case study in the petrochemical industry that companies face multiple challenges in dealing with technology intelligence and need a systematic framework for managing this process.

2.2 High-Tech Companies and Technology Scouting Challenges

Due to their inherent nature, high-tech companies continuously encounter multiple challenges in monitoring and predicting technological developments. These companies operate in an environment where rapid technological changes, high uncertainty, and multiple risks are key characteristics. Hajigholam et al. [19] showed in their research that science and technology parks are always seeking to improve their systems and structures for creating, growing, and sustaining technology companies. One of their necessities is improving technology scouting and development processes.

Failure to monitor technological developments in a timely manner can pose significant risks for these companies. Zargar et al. [20] demonstrated in their study that the increasing complexity of supply chains and the importance of resilience in facing various risks necessitate careful examination of factors affecting risk management. They identified "information management and transparency" and "operational flexibility and resilience" as key factors in this area.

Van Minnebruggen and Lippens [5] believe that scientists and research institutions must keep pace with rapidly evolving technologies and methods. They emphasize that only a strong collaborative approach between technology experts and researchers can bring together all essential elements in the technology cycle - from scouting to risk reduction and implementation. This becomes particularly important in implementing intelligent systems, as Mokhtari et al. [21] have shown that implementing prediction and data collection systems is essential for improving reliability and cost efficiency.

Nezamipour et al. [22] concluded in their study that organizations have an urgent need for technology scouting in terms of mission-related conditions, and under vulnerable conditions, the achievement of the organization's mission in technology development and innovation faces challenges. Parsaei [23] emphasizes in their research that assessing information security awareness and identifying vulnerabilities is essential for evaluating organizational cybersecurity risk.

2.3 AI and Its Applications in Technology Scouting

Recent advancements in AI have created new opportunities in technology scouting methodologies. Armenia et al. [3] demonstrate an increasing organizational trend toward leveraging AI capabilities for analyzing and solving complex problems. AI's capabilities in processing massive amounts of data, identifying hidden patterns, and predicting future trends have transformed it into a powerful tool for technology scouting.

Mühlroth and Grottke [10] have presented an AI-based data mining model that helps companies identify emerging topics and trends with a higher level of automation than before. This model also incorporates self-adaptive capabilities that allow it to update itself as new data becomes available automatically. From a risk management perspective, Karbasishargh et al. [24] indicate that using AI can help increase system reliability, reduce and control risks, and optimize safety.

Sahoo et al. [4] demonstrated in their research that AI capabilities have a favorable impact on open innovation practices, which subsequently leads to improved business performance. Their analysis of the moderating effect of environmental dynamism showed that this factor significantly influences the relationship between AI capabilities and outbound open innovation. Moghimi Esfandabadi et al. [25] emphasize that technological innovation in AI can help reduce operational risks.

Schuh et al. [26] addressed the challenge of dealing with information overflow in technology management in their study. They presented a concept for combining information retrieval solutions in a new intelligent approach. Similarly, Mariani et al. [6] conducted a systematic review of 1,448 articles, mapping the field in terms of dominant topics and their evolution over time. It provided an interpretive framework to clarify the drivers and implications of AI adoption for innovation.

However, Stahl et al. [8], in their Delphi study with AI experts, pointed to ethical and human rights challenges in using AI. They emphasize that the discussion around ethics in AI would benefit from redefining and placing a stronger emphasis on the systemic nature of AI ecosystems.

In the Industry 5.0 era, the integration of AI capabilities with human capabilities has gained special importance. Zamany et al. [27] demonstrated in their research that an intelligent combination of AI capabilities and human competencies can lead to improved technology transfer processes, enhanced human capabilities, improved human-machine interaction, and knowledge and innovation management.

2.4 Risk Assessment and Reliability in Technology Scouting

The technology scouting process in high-tech companies requires precise risk assessment and reliability assurance. Moghimi Esfandabadi et al. [25] have identified five key dimensions for enhancing safety, reliability, and performance in industries, encompassing diversity, technological innovation, infrastructure, human resources, and coordination. In this context, Zamany et al. [27] emphasize that organizations should focus on investing in advanced AI system development, training and empowering human resources, and establishing integrated knowledge management systems.

One of the main challenges in technology scouting is managing risks associated with prediction and decision-making. Zargar et al. [20] demonstrated in their study that the existence of technical infrastructure and expert human resources, as well as product traceability capabilities, are among the most important factors in risk management. This becomes particularly important when organizations face massive volumes of technological data.

Nezamipour et al. [22] showed in their research that organizations have relatively low capabilities in technology scouting, and this vulnerable condition can challenge the organization's mission fulfillment. To address this challenge, Mokhtari et al. [21] suggest using fuzzy clustering methods for equipment maintenance, which can help improve reliability and cost efficiency.

Security and data protection is another important aspect of risk assessment in technology scouting. Parsaei [23] emphasizes in their research that assessing information security awareness and identifying users who are more vulnerable to social engineering attacks is essential for evaluating organizational cybersecurity risk. This becomes particularly important when organizations use intelligent systems for technology scouting.

Risk assessment in technology scouting has gained international attention across various domains. Lemos et al. [28] analyzed environmental risk assessment and management in Industry 4.0, emphasizing the integration of IoT technologies for real-time monitoring and smart solutions to reduce workplace accidents. Their work demonstrates how AI-driven systems can enhance safety protocols in industrial environments. Shanmugam and Azam [29] conducted a comprehensive review of risk assessment methodologies for heterogeneous Internet of Medical Things (IoMT) devices, highlighting the challenges of applying existing frameworks to emerging technologies and the need for adaptive risk assessment approaches.

In the financial sector, Javaid [30] explored AI-driven predictive analytics for transforming risk assessment and decision-making, showing how machine-learning algorithms can forecast market trends and potential threats with unprecedented accuracy. This research demonstrates the critical role of proactive risk management in financial institutions. Luo et al. [31] developed fuzzy logic and neural network-based risk assessment models for import and export enterprises, addressing the challenges of large-scale data processing and inherent uncertainty in international trade environments.

Furthermore, Cantelli-Forti et al. [32] presented a comprehensive approach to critical infrastructure protection, combining cyber-attack detection with physical threat assessment using advanced sensor technologies. Their SCOUT system demonstrates the importance of multi-layered security approaches in protecting critical technological assets. These international studies collectively emphasize that effective risk assessment in technology-intensive environments requires sophisticated AI-driven approaches capable of handling uncertainty, large-scale data, and real-time threat detection.

To increase reliability in technology scouting, organizations must adopt an integrated and balanced approach in combining AI capabilities with human competencies. Karbasishargh et al. [24] introduce novel strategies for increasing reliability and safety through advanced technologies like AI. These strategies include identifying reliability criteria, risk management and control methods, and new and creative techniques for enhancing safety under various conditions.

2.5 Literature Review Summary

A review of the literature shows that technology scouting in the current era faces multiple complexities and challenges that have made traditional approaches inefficient. Although numerous studies have been conducted in the field of technology scouting and AI applications, there is still a significant gap in providing a comprehensive and systematic framework for AI-based technology scouting that simultaneously addresses technical, organizational, and risk management dimensions.

Analysis of the literature indicates that a successful AI-based technology scouting process requires simultaneous attention to several key dimensions: First, identifying and precisely defining technology scouting goals and strategies; second, designing and implementing intelligent systems with high reliability; third, effective data and information management; fourth, analysis and extraction of meaningful insights; and fifth, continuous evaluation and improvement of the process.

This summary confirms the necessity of conducting the present research with the aim of identifying and analyzing key themes and components in the AI-based technology scouting process for proper R&D project definition and risk reduction. Such a framework can help high-tech companies design and implement intelligent scouting systems with high reliability while simultaneously reducing risks associated with technological decision-making.

3. Research Methodology

The thematic analysis method was employed to achieve the objectives of this research. Thematic analysis is one of the common methods in qualitative analysis that focuses on identifying, analyzing, and reporting patterns within qualitative data. This method can go beyond counting explicit words and phrases in the text to extract implicit meanings and concepts from the data [33].

The research population consists of scientific articles published in the field of AI-based technology scouting between 2014 and 2024. Initially, a comprehensive and systematic review of the subject literature was conducted, leading to the identification of 298 initial articles. These ten years were selected due to rapid developments in AI and advanced technologies in recent years.

A set of specialized keywords was used in reputable scientific databases to access relevant articles, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The keywords used included Technology scouting, AI, AI-based technology scouting, High technology, Advanced technology, and other related terms.

The retrieved articles were evaluated based on multiple criteria. These criteria included title, abstract, content, article details, and other relevant characteristics. In this process, articles that did not align with the main research questions and objectives were removed from the review set. This process led to the identification and collection of 70 articles relevant to the research topic.

The main criteria for article selection or rejection were:

- Research language: Only English-language articles were considered
- Study timeframe: Articles published between 2014 and 2024
- Study conditions: Focus on studies addressing technology scouting and the use of AI in this field
- Study population: High-tech and technology-oriented companies
- Article type: Research articles, review articles, and case studies published in reputable scientific journals

In the final stage, the full text of selected articles was prepared for deeper analysis. This stage included extracting and digitizing key sections of articles, including abstract, introduction, methodology, findings, and conclusion. The thematic analysis process was conducted in six main steps:

1. Data familiarization: Deep and repeated study of texts for a complete understanding of content
2. Initial coding generation: Systematic coding of data and identification of interesting features
3. Theme search: Categorizing codes and collecting data related to each potential theme
4. Theme Review: Examining the relationship of themes with codes and datasets
5. Theme definition and naming: Continuous analysis to refine details of each theme
6. Report preparation: Selection of compelling data examples and final analysis

To ensure the validity and reliability of findings, various methods were used, such as peer review by research colleagues, recording of part of the data by a second researcher, and comparison of results. Additionally, specialized qualitative data analysis software was used to increase the accuracy of analyses.

4. Research Findings

In this section, the findings from the thematic analysis are presented step by step. At each stage, the analysis process and its results are explained.

4.1 First Step: Data Familiarization

In this stage, the researcher conducted repeated readings of the information content to gain a deep understanding. Through an initial review of article content, five main subject areas were identified:

- AI technologies in technology scouting
- Technology scouting processes
- AI applications in technology scouting
- Challenges and considerations
- Advanced industries and application domains

Through careful examination of each area's content and their interrelationships, the foundation for identifying initial codes and themes was established. By analyzing the identified areas, the relative importance of each area was estimated, as shown in Figure 1.

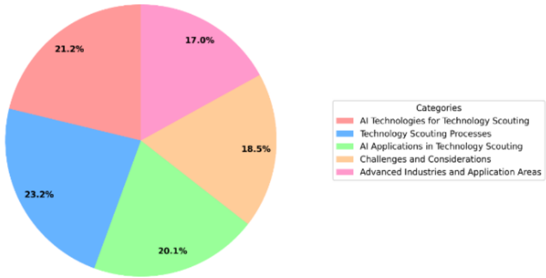

Figure 1. Main Subject Areas and Their Relative Importance in AI-Based Technology Scouting

4.2 Second Step: Data Coding

In this stage, based on findings from the previous stage, systematic data coding was conducted. Initial codes were extracted through careful analysis of each area's content and identification of key concepts. These codes served as the basis for discovering themes in subsequent stages. Part of the extracted codes from each area is presented in Table 1.

Table 1. Coding of Data Related to AI-Based Technology Scouting for R&D Risk Reduction

Area	Identified Codes	Ref.
AI Technologies in Technology Scouting (55 codes)	Machine learning, deep neural networks, natural language processing, computer vision, reinforcement learning, expert systems, genetic algorithms, fuzzy logic, swarm intelligence, robotic process automation, cognitive computing, pattern recognition, optimization, clustering, transfer learning, topic modeling, sentiment analysis	[3, 4, 6, 10, 26, 30, 34, 35, 36, 37]
Technology Scouting Processes (60 codes)	Environmental scanning, SWOT analysis, trend analysis, problem-solving, technological forecasting, needs identification, technology mapping, future studies, intellectual property, scenario planning, strategic management, competitive intelligence, patent analysis, innovation management, risk assessment, benchmarking, gap analysis, networking, technology transfer, knowledge management, information management, project management.	[2, 7, 17, 18, 38, 39, 40, 41, 42, 43]
AI Applications in Technology Scouting (52 codes)	Trend prediction, emerging pattern detection, scientific text analysis, patent information extraction, social network analysis, expert identification, market sentiment analysis, knowledge mapping, technological milestone prediction, weak signal detection, technology clustering, co-occurrence analysis, complex data visualization, automated report generation	[10, 44, 45, 46, 47, 48, 49, 50, 51, 52]
Challenges and Considerations (48 codes)	Data privacy, AI ethical issues, cybersecurity, data dependency, algorithmic bias, AI model explainability, system scalability, integration with existing systems, prediction reliability, computational complexity, need for multiple expertise, result validation, decision-making transparency, user trust in the system, data quality and validity, continuous learning and updating, adaptation to rapid technological changes.	[5, 8, 11, 23, 28, 29, 31, 32, 53, 54, 55, 56, 57]
Advanced Industries and Application Domains (44 codes)	AI and machine learning, Internet of Things, blockchain, quantum computing, advanced robotics, nanotechnology, biotechnology, additive manufacturing and 3D printing, smart materials, autonomous vehicles, electric vehicles, drones and unmanned systems, renewable energies, fintech and digital banking, digital health technologies, smart agriculture, aerospace and defense, space exploration, cybersecurity, digital education, genetic engineering	[22, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72]

Network diagrams were used to represent the relationship between codes and areas visually. Network diagrams related to extracted codes in the area of AI technologies in technology scouting and also advanced industries and application domains are presented in Figure 2 and Figure 3.

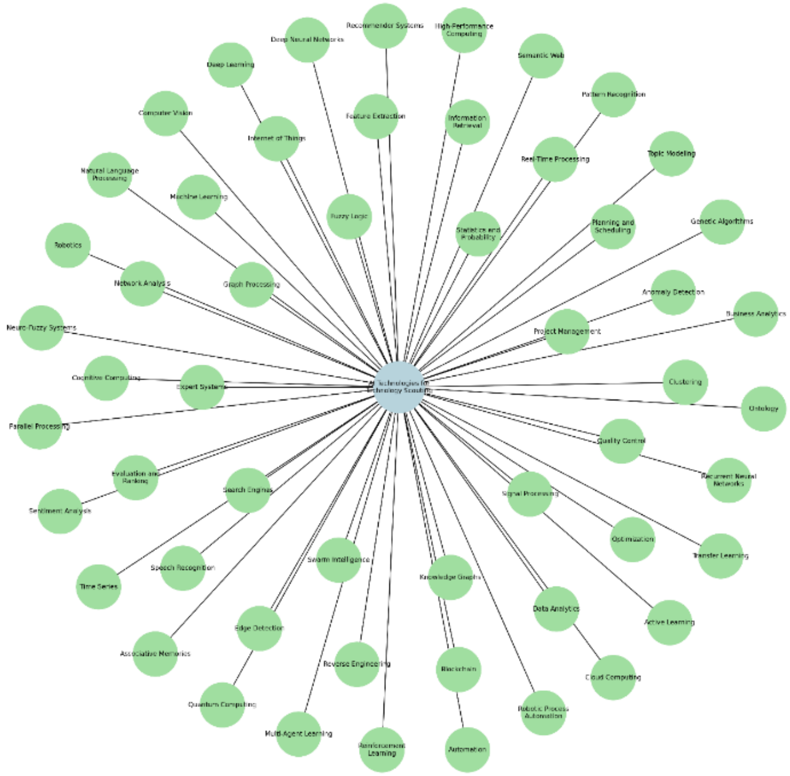

Figure 2. Network Diagram of Codes Related to AI Technologies in Technology Scouting for R&D Risk Reduction

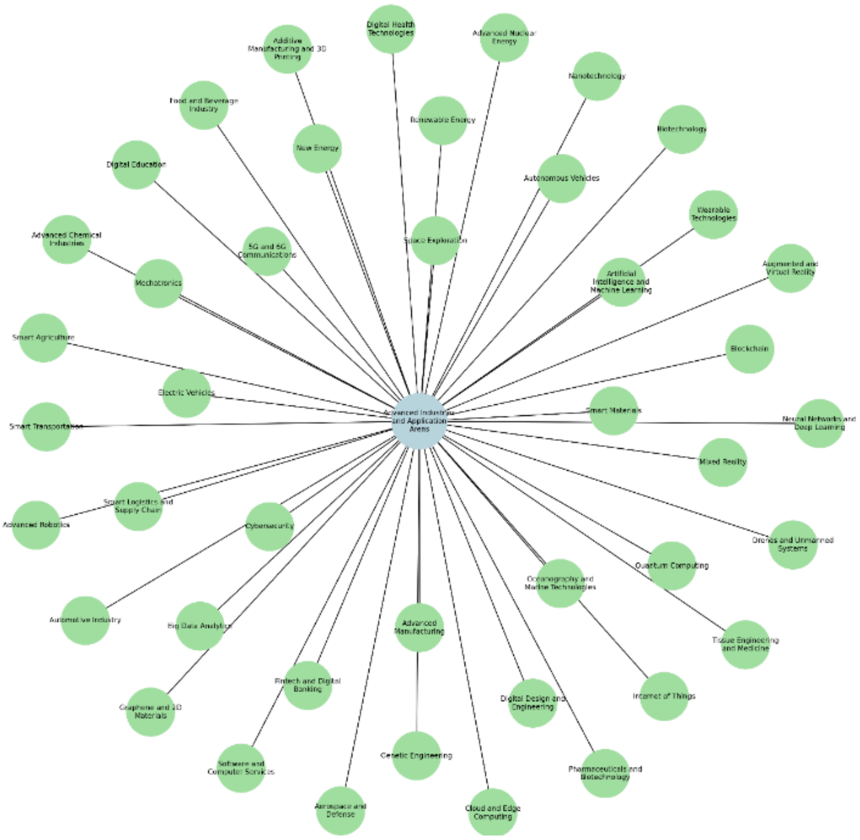

Figure 3. Network Diagram of Codes Related to Advanced Industries and Application Domains in Technology Scouting for R&D Risk Reduction

4.3 Third Step: Theme Extraction

In this stage, through meticulous examination of codes identified in the previous step, themes were discovered and generated. Initially, among approximately 327 initial codes, 68 codes that were repetitive or very similar were identified and removed. This process helped increase accuracy and reduce unnecessary complexity in the analysis. Then, the theme extraction process was conducted in two main phases:

1. Identifying sub-themes: Through analysis and examination of the remaining 259 codes, sub-themes were identified. These sub-themes represent common concepts and recurring patterns among the codes.
2. Identifying main themes: After identifying sub-themes by examining their relationships and similarities, main themes were extracted. These main themes are more comprehensive concepts that encompass sub-themes. Part of the results from this section are presented in **Error! Not a valid bookmark self-reference.**.

Table 2. Main Themes, Sub-themes, and Related Codes in AI-Based Technology Scouting for R&D Risk Reduction

Main Themes	Sub-themes	codes
Strategic Goal Setting	Defining technological vision	Environmental scanning, future studies, technological forecasting
	Setting short-term and long-term goals	Strategic planning, portfolio management, SWOT analysis
	Alignment with the organization's overall strategy	Strategic management, systems thinking, business modeling
Industry Trend Analysis	Review of industry reports	Competitive intelligence, trend analysis, environmental scanning
	Competitor analysis	Competitive intelligence, competitor analysis, benchmarking
	Identifying emerging technologies	Emerging pattern detection, technological milestone prediction, weak signal detection
Selection of Appropriate Algorithms	Review of machine learning algorithms	Machine learning, deep neural networks, reinforcement learning
	Selection of natural language processing methods	Natural language processing, scientific text analysis, patent information extraction
	Assessment of network analysis techniques	Social network analysis, co-occurrence analysis, knowledge mapping
Data Access Protocol Design	Determining data extraction methods	Web crawling, data extraction, data mining techniques
	ETL process design	Extract, transform and load data, data integration, and data cleaning.
	Access permission management	Access control, data security, identity and access management
Design and Implementation of Smart Crawlers	Development of intelligent search algorithms	Search engines, information retrieval, ranking algorithms
	Crawl speed and efficiency optimization	Algorithm optimization, computational resource management, parallel processing
	Compliance with ethical and legal crawling protocols	AI ethics, intellectual property rights, privacy protection
Automated Text and Image Extraction	Advanced OCR implementation	Text detection in images, image processing, computer vision
	Text extraction from PDF files and images	Document processing, structured information extraction, format conversion
	Table and chart identification and extraction	Document structure analysis, visual data extraction, image processing
Natural Language Processing for Information Extraction	Keyword extraction	Text analysis, concept extraction, natural language processing
	Entity and relationship detection	Information extraction, semantic analysis, modeling
	Automated text summarization	Natural language processing, key concept extraction, automated text generation

Main Themes	Sub-themes	codes
Data Preprocessing and Cleaning	Removal of duplicate and noisy data	Data cleaning, noise removal, data quality improvement
	Format standardization	Data integration, format conversion, data quality management
	Incomplete data completion	Data reconstruction, missing data estimation, data incompleteness analysis
Sentiment and Opinion Analysis	Opinion polarity identification	Sentiment analysis, natural language processing, user opinion analysis
	Sentiment trend analysis	Temporal sentiment analysis, attitude change prediction, trend analysis
	Hot and controversial topic identification	Topic analysis, emerging trend identification, social media monitoring
Pattern Detection and Clustering	Identifying related technology groups	Technology clustering, technology mapping, relationship analysis
	Hidden trend discovery	Hidden data analysis, deep learning, pattern discovery algorithms
	Source and reference clustering	Citation analysis, scientific source clustering, knowledge mapping
Social and Communication Network Analysis	Identifying key individuals and organizations	Social network analysis, thought leader identification, influence analysis
	Collaboration pattern analysis	Collaboration network analysis, co-authorship patterns, organizational communication analysis
	Research community discovery	Network community detection, research group analysis, scientific mapping
Patent Analysis and Technology Mapping	Patent registration trend analysis	Patent analysis, innovation trend prediction, R&D activity assessment
	Identifying key patent areas	Patent mapping, patent portfolio analysis, innovation opportunity identification
	Technology relationship mapping	Technology mapping, technological dependency analysis, technology convergence analysis

4.4 Fourth Step: Theme Review

In this stage, the identified themes were subjected to review and reassessment. This review included:

1. Checking themes' alignment with original data
2. Evaluating internal relationships between themes
3. Modification, combination, separation, or deletion of themes when necessary

After this review, the final themes were formed that appropriately describe the research data and establish logical relationships between them.

4.5 Fifth Step: Theme Definition and Naming

In this stage, using the analyses conducted and considering the specific nature of AI-based technology scouting in high-tech companies, precise definitions and naming of themes were undertaken. After careful reviews and consultation with the research team, the themes were organized in a three-layer structure:

1. First Layer: Main stages of AI-based technology scouting process
2. Second Layer: Main themes
3. Third Layer: Sub-themes

A combination of existing models in the literature and findings from thematic analysis was used to determine the main stages of the AI-based technology scouting process. After comprehensive reviews, an 11-stage model was selected as the main framework. These stages are:

1. Defining technology scouting strategy and objectives
2. Identifying key technology areas
3. Designing and implementing AI systems for technology scouting
4. Selection and integration of data sources
5. Automated data collection using AI
6. Data processing and analysis with advanced algorithms
7. Insight and hidden pattern extraction

8. Evaluation and validation of results
9. Decision-making and strategic planning
10. Implementation and execution of decisions
11. System feedback and continuous improvement

4.6 Sixth Step: Presenting Findings

Based on the conducted analyses, the final model of AI-based technology scouting in high-tech companies is presented in **Table 3**.

Table 3. Qualitative Process Model of AI-Based Technology Scouting in High-Tech Companies for R&D Risk Reduction

Technology Scouting Process Stages	Main Themes	Sub-themes
Defining Technology Scouting Strategy and Objectives	Strategic Goal Setting	Defining technological vision
		Setting short-term and long-term goals
		Alignment with the organization's overall strategy
	Identifying Organizational Needs	Value chain analysis
		Current capabilities assessment
		Identifying technological gaps
	Determining Scouting Time Horizon	Setting short-term, medium-term, and long-term periods
		Setting information update frequency
	Determining Resources and Budget	Hardware and software cost estimation
		Expert human resource allocation
		Budget determination for data purchase and database subscriptions
Identifying Key Technology Areas	Industry Trend Analysis	Review of industry reports
		Competitor analysis
		Identifying emerging technologies
	Assessment of Organization's Current Capabilities	Internal technology audit
		Knowledge and skills assessment
		Technical infrastructure review
	Identifying Technological Gaps	Comparison with industry best practices
		Performance gap analysis
		Future technological needs identification
	Prioritizing Technological Areas	Strategic importance analysis
		Growth potential assessment
		Technical and economic feasibility study
Designing and Implementing AI Systems for Technology Scouting	Selection of Appropriate Algorithms	Review of machine learning algorithms
		Selection of natural language processing methods
		Assessment of network analysis techniques
	System Architecture Design	Database structure design
		Software module determination
		User interface design
	Development of Machine Learning Models	Training prediction models
		Development of clustering algorithms
		Implementation of recommender systems
	Integration with Existing Systems	API design
		Data synchronization
		Security and access management
Selection and Integration of Data Sources	Identification of Relevant Data Sources	Review of scientific databases
		Identification of news and media sources
		Review of patent databases
		Source credibility review

Technology Scouting Process Stages	Main Themes	Sub-themes
	Assessment of Source Quality and Credibility	Data comprehensiveness assessment
		Information currency review
	Data Access Protocol Design	Determining data extraction methods
		ETL process design
		Access permission management
	Integration of Heterogeneous Data Sources	Data format standardization
		Creating a unified data model
		Resolving data conflicts
Automated Data Collection Using AI	Design and Implementation of Smart Crawlers	Development of intelligent search algorithms
		Crawl speed and efficiency optimization
		Compliance with ethical and legal crawling protocols
	Automated Text and Image Extraction	Advanced OCR implementation
		Text extraction from PDF files and images
		Table and chart identification and extraction
	Natural Language Processing for Information Extraction	Keyword extraction
		Entity and relationship detection
		Automated text summarization
	Management and Storage of Collected Data	Design of scalable storage structure
		Implementation of data versioning system
		Application of privacy policies
Data Processing and Analysis with Advanced Algorithms	Data Preprocessing and Cleaning	Removal of duplicate and noisy data
		Format standardization
		Incomplete data completion
	Sentiment and Opinion Analysis	Opinion polarity identification
		Sentiment trend analysis
		Hot and controversial topic identification
	Pattern Detection and Clustering	Identifying related technology groups
		Hidden trend discovery
		Source and reference clustering
	Social and Communication Network Analysis	Identifying key individuals and organizations
		Collaboration pattern analysis
		Research community discovery
Insight and Hidden Pattern Extraction	Identifying Emerging Trends	Keyword frequency analysis over time
		Identification of fast-growing technologies
		Prediction of technological milestones
	Patent Analysis and Technology Mapping	Patent registration trend analysis
		Identifying key patent areas
		Technology relationship mapping
	Future Technology Path Prediction	Using time series prediction models
		Simulation of different scenarios
		Prediction sensitivity analysis
	Identification of Technological Opportunities and Threats	Data-driven SWOT analysis
		Identifying technological gaps
		Technological risk assessment
Evaluation and Validation of Results	Testing and Validation of Models	Running statistical tests
		Cross-validation of models
		Testing prediction robustness
		Conducting assessment sessions with experts

Technology Scouting Process Stages	Main Themes	Sub-themes
	Expert Opinion Comparison	Matching results with industry reports
		Collecting end-user feedback
	Prediction Accuracy and Validity Assessment	Calculating prediction accuracy metrics
		Comparing with actual data over time
		Prediction error analysis
	Error and Bias Identification and Resolution	Examining algorithmic biases
		Model modification to reduce errors
		Implementation of self-correction mechanisms
Decision-making and Strategic Planning	Result Interpretation for Decision Makers	Preparing analytical reports
		Designing management dashboards
		Providing strategic recommendations
	Strategic Option Assessment	Cost-benefit analysis of options
		Strategy risk assessment
		Simulation of each option's consequences
	Technology Strategy Development	Determining investment priorities
		Designing technology roadmap
		Determining cooperation and competition strategies
	Technology Acquisition and Development Planning	Determining acquisition methods
		Planning R&D projects
		Determining resources needed for technology development
Implementation and Execution of Decisions	Resource Allocation for Strategy Implementation	Technology project budgeting
		Expert human resource allocation
		Providing the required technical infrastructure
	Technology Project Management	Work breakdown structure design
		Time and cost management
		Quality control and risk management
	Technological Partnerships and Collaborations	Identifying potential partners
		Negotiation and development of cooperation agreements
		Joint project management
	Implementation and Integration of New Technologies	Technology transfer process design
		Staff training and empowerment
		Integration with existing systems
System Feedback and Continuous Improvement	User Feedback Collection	Design of automated feedback mechanisms
		Conducting user assessment sessions
		Analysis of system usage patterns
	System Performance Evaluation	Definition and calculation of key performance indicators (KPIs)
		Comparison of performance with set goals
		Identification of system strengths and weaknesses
	Algorithm Updates and Improvements	Model retraining with new data
		Algorithm parameter optimization
		Implementation of new algorithms

Technology Scouting Process Stages	Main Themes	Sub-themes
	Continuous System Learning and Adaptation	Implementation of reinforcement learning mechanisms
		Automatic adaptation to environmental changes
		Continuous improvement of system accuracy and efficiency

To ensure the validity and reliability of findings from thematic analysis, the following measures were taken:

- To ensure content validity, the analyzed data were selected from credible and relevant sources in the field of AI-based technology scouting. Additionally, all stages of thematic analysis were reviewed by the research team, consisting of the researcher and supervisory and advisory professors.
- Two independent coders were used to analyze part of the data to confirm convergent validity. The level of agreement between coders was calculated using the Kappa coefficient, which was found to be 0.81, indicating acceptable agreement.
- To ensure the reliability of findings, the thematic analysis process was carefully documented. This documentation includes a detailed description of data preprocessing stages, selection method of analysis units, coding method, theme creation and organization method, and other process details.

The thematic analysis process and its findings were reviewed by two expert professors in the fields of technology management and AI. The feedback provided by these experts led to minor modifications in the structure and naming of some themes.

5. Discussion and Conclusion

This research was conducted with the aim of identifying and analyzing key themes and components in the AI-based technology scouting process in high-tech companies to reduce R&D project risks. The research findings indicate that technology scouting in the AI era is a complex and multidimensional process requiring simultaneous attention to technical, organizational, and managerial aspects. The identification of 11 main stages, 44 primary themes, and 132 sub-themes in this research demonstrates the complexity and breadth of this process.

Analysis of the findings suggests that success in implementing AI-based technology scouting systems requires understanding and proper management of complex interactions between various factors. In this regard, the research findings can be discussed at several levels. At the strategic level, the findings show that alignment of the technology scouting process with the organization's overall strategy is of vital importance. This finding aligns with the results of Wang and Quan [2], who emphasized the importance of strategic integration in technology management. High-tech companies must design their scouting process in a way that directly supports the organization's strategic objectives.

At the organizational level, the findings indicate that establishing appropriate structures and processes to support intelligent technology scouting is essential. This aligns with the research of Sen et al. [11], who emphasized the importance of organizational readiness in adopting and implementing intelligent systems. The model presented in this research provides a comprehensive framework for organizing these structures and processes.

At the technical level, the present research highlights the importance of proper selection and implementation of AI technologies. This finding corresponds with the results of Armenia et al. [3], who demonstrated that success in AI implementation requires a deep understanding of this technology's capabilities and limitations. In particular, the findings show that an appropriate combination of machine learning algorithms, natural language processing, and network analysis can help increase the effectiveness of the scouting process.

In terms of risk management and reliability, the research findings demonstrate the importance of a comprehensive approach to risk management. This finding aligns with the results of Moghimi Esfandabadi et al. [25] and Karbasishargh et al. [24], who emphasized the importance of integrating risk management into all organizational processes. The model presented in this research provides multiple mechanisms for identifying, evaluating, and managing risks related to technology scouting.

The comprehensive AI-based technology scouting model developed in this research presents a sophisticated three-layer architectural framework designed to minimize R&D project risks in high-tech companies systematically. As illustrated in Figure 4, the model operates through three interconnected layers: the Strategic Layer (encompassing strategy definition and key technology area identification), the Technical and Analytical Layer (covering AI system implementation, data processing, and insight extraction), and the Operational and Executive Layer (focusing on decision-making, implementation, and continuous improvement).

The model demonstrates a cyclical process flow that begins with diverse input data sources, including patent databases (WIPO, USPTO, EPO, JPO), academic and scientific resources, market and industry data, and media and social networks. These data sources feed into an 11-stage systematic process that progresses from strategic goal setting through automated data collection and advanced analytical processing to final implementation and continuous system improvement. Critical feedback loops ensure adaptive learning and risk mitigation throughout the process. At the same time, the integration of AI capabilities at each technical stage enables real-time processing, pattern recognition, and predictive analytics. This systematic approach transforms raw technological intelligence into actionable strategic insights while maintaining continuous monitoring and adaptation capabilities essential for high-tech environments.

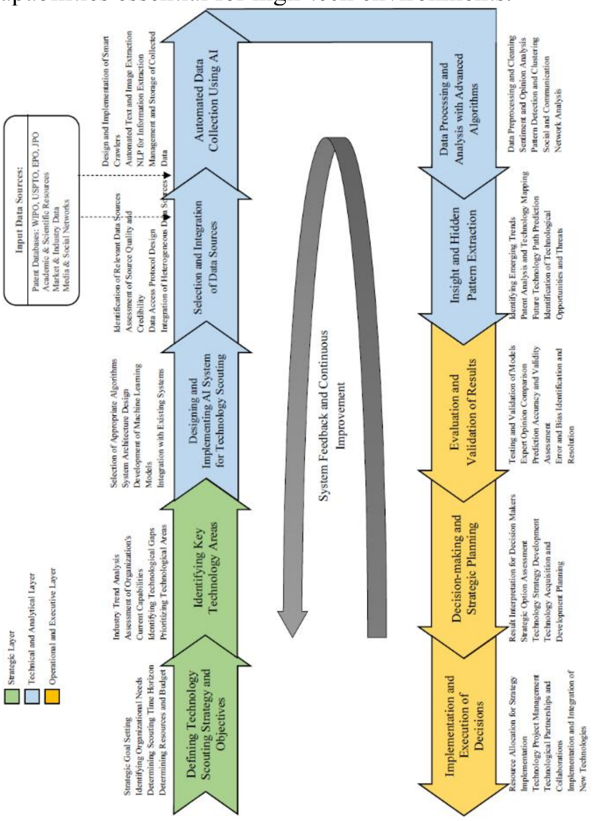

Figure 4. Comprehensive AI-Based Technology Scouting Process Model for R&D Risk Reduction in High-Tech Companies

In the area of data security and protection, the research findings align with Parsaei [23], who emphasized the importance of assessing information security awareness and identifying cybersecurity vulnerabilities. The model presented in this research provides a comprehensive framework for data security management in the technology scouting process.

One of the important findings of this research is identifying the importance of continuous learning and adaptation in the technology scouting process. This finding aligns with the results of Zamany et al. [27], who emphasized the importance of the intelligent combination of AI capabilities and human competencies. The model presented in this research provides multiple mechanisms for continuous system learning and improvement.

In the area of knowledge management and organizational learning, the research findings indicate that success in technology scouting requires creating effective systems for knowledge management and sharing. This finding aligns with the results of Uygur and Ferguson [9], who emphasized the importance of knowledge management in innovation ecosystems.

The practical applications of this research can be considered at several levels; at the senior management level, the presented model can serve as a framework for developing technology scouting strategies and resource allocation. Managers can use this model to ensure that all key aspects of the technology scouting process are considered. At the middle management and implementation team level, the model can serve as a guide for designing and implementing intelligent technology scouting systems. The sub-themes identified in this research provide practical guidance for implementing each stage of the scouting process. At the technical expert level, the research findings can serve as a guide for selecting and implementing appropriate technologies. The presented model provides criteria for evaluating and selecting AI algorithms and tools.

The limitations of this research can be divided into several categories: methodological limitations, including focus on thematic analysis, and limitations in qualitative results generalizability. Data limitations include a focus on English-language articles and time limitations in article review. Content limitations include a lack of examination of contextual factors such as organization size, industry type, and environmental conditions in the technology scouting process.

For future research, it is suggested that the presented model be empirically tested in different companies and its effectiveness be evaluated through in-depth case studies or quantitative research with large samples. Additionally, the development of quantitative indicators for evaluating the performance of intelligent technology scouting systems, including financial, operational, and strategic indicators, could be the subject of future research. Furthermore, examining the impact of contextual factors such as organization size, industry type, and environmental conditions on the effectiveness of technology scouting systems could help better understand the success conditions of these systems.

Research on the role of organizational culture and human factors in the success of intelligent technology scouting systems, including examining resistance to change, training needs, and motivational factors, could also be a suitable area for future research. Researchers could also investigate ethical and legal challenges in using AI in technology scouting, including issues related to privacy, intellectual property, and accountability. The development of predictive models for evaluating the success of implementing these systems and studying the role of inter-organizational collaborations in increasing technology scouting effectiveness, including examining collaboration models, data exchange, and knowledge sharing, could also add to the richness of knowledge in this field.

Conflict of Interests

The Authors declares that there is no conflict of interest.

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