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STRATEGIC FORECASTING METHODS FOR MICRO AND NANOTECHNOLOGIES

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Abstract. Strategic forecasting is essential for decision-making in the knowledge-based economy, where rapid technological change demands structured anticipation. This paper critically reviews the main forecasting methods used for micro and nanotechnologies and evaluates their theoretical basis, strengths, and limitations. A systematic literature review covers quantitative approaches, including time-series extrapolation, S-curve diffusion models, bibliometric analysis, and patent-landscape analysis, as well as qualitative methods such as the Delphi technique, scenario planning, strategic roadmapping, and expert judgment. Hybrid and AI-enhanced frameworks are also examined. The review shows that quantitative methods are objective but largely retrospective, whereas qualitative methods are flexible but vulnerable to bias and limited validation. Hybrid approaches appear most promising, yet they remain unevenly implemented. The identified methodological gaps support the development of an integrated, adaptive forecasting framework for emerging technologies.

Keywords: foresight, Delphi technique, scenario planning, patent analysis, pasteurization process.

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1. Introduction

In the contemporary knowledge-based economy, the capacity to anticipate technological evolution has become a critical competitive advantage. Organizations and research institutions that adopt structured forecasting methodologies are better positioned to allocate resources efficiently, minimize investment risk, and exploit emerging opportunities (Martino, 1993; Fildes and Goodwin, 2007). Strategic forecasting provides this perspective through systematic analytical frameworks that integrate historical data, expert knowledge, and scenario construction to support long-term decision-making.

Micro and nanotechnologies - encompassing microelectronics, MEMS/NEMS, nanomaterials, and nanoelectronics - represent domains of particularly high complexity for forecasting. These fields are characterized by rapid innovation rates, strong interdisciplinary convergence, and radical uncertainty regarding adoption trajectories and regulatory environments (Georghiou *et al.*, 2008; Miles, 2010). Classical single-method forecasting approaches, whether purely quantitative or exclusively qualitative, systematically fail to capture the multidimensional dynamics of these emerging domains.

The objective of this paper is to present a structured critical analysis of strategic forecasting methods applicable to micro and nanotechnology domains, evaluating the strengths and limitations of each approach and identifying the methodological gaps that motivate the development of a novel integrated forecasting framework within ongoing doctoral research.

2. Classification of strategic forecasting methods

Strategic forecasting methods fall into three main categories - quantitative, qualitative, and hybrid - each with distinct epistemological foundations, data requirements, and applicability conditions (Martino, 1993; Georghiou *et al.*, 2008). The choice of method depends on data availability, degree of uncertainty, and strategic objectives.

It is important to distinguish the related concepts of forecasting, foresight, and strategic intelligence. Forecasting provides objective, quantifiable predictions from historical data and mathematical models. Foresight adopts a qualitative, prospective orientation, constructing multiple alternative futures through expert deliberation. Strategic intelligence integrates both approaches, collecting and interpreting diverse information to support holistic decision-making (Miles, 2010; Porter and Cunningham, 2005). In practice, the most robust frameworks combine elements of all three.

Table 1 summarizes the three methodological categories and their key characteristics.

Table 1
Comparative overview of strategic forecasting method categories

Category	Main methods	Strengths	Limitations
<i>Quantitative</i>	<i>Time series, S-curves, bibliometrics, patent analysis</i>	<i>Objective, replicable, measurable maturity indicators</i>	<i>Retrospective; inadequate for disruptive/emergent technologies</i>
<i>Qualitative</i>	<i>Delphi, scenario planning, roadmapping, expert judgment</i>	<i>Handles radical uncertainty; integrates expert knowledge</i>	<i>Susceptible to bias; limited standardization; hard to validate ex-post</i>
<i>Hybrid / AI</i>	<i>Bibliometrics + Delphi, patents + scenarios, ML, NLP, GNN</i>	<i>Cross-validates; scalable; captures non-linear dynamics</i>	<i>Inconsistent implementation; opacity; few validated frameworks</i>

3. Quantitative forecasting methods

3.1. Time series extrapolation and S-curve models

Time series extrapolation - including ARIMA models and multiple regression - provides a quantitative basis for estimating technological growth from historical data on publications, patents, or market indicators (Daim *et al.*, 2006). These methods are most effective when technology evolution is relatively stable and well-documented, but presuppose data continuity and are poorly suited to radical discontinuities or emergent technologies with sparse historical records.

S-curve diffusion models describe technological adoption as a sigmoidal function of time. The standard logistic model is expressed as:

$$N(t) = \frac{K}{1 + e^{-r(t-t_0)}} \quad (1)$$

where: K is the saturation level, r the growth rate, and t_0 the inflection point (Bengisu and Nekhili, 2006).

The Gompertz variant introduces asymmetry with slower initial growth, making it more realistic for nanotechnologies with extended development cycles (Bengisu and Nekhili, 2006). Both models have been applied to microelectronics scaling, MEMS/NEMS sensor adoption, and nanomaterial commercialization, identifying critical investment windows. Key limitations include sensitivity to parameter estimation, inability to capture exogenous shocks, and inadequacy for very early-stage technologies.

Figure 1 presents a logistic S-curve model fitted to historical nanomaterial commercial adoption data (2005-2025) and projected through 2035. The model parameters ($K = 92.3\%$, $r = 0.466$, $t_0 = 2013.5$) indicate that market

saturation approaches asymptotically, with the inflection point occurring in 2013-2014. This validates the theoretical framework in equation (1) and confirms that nanomaterial adoption followed classical diffusion dynamics, though regulatory barriers delayed full saturation beyond initial projections.

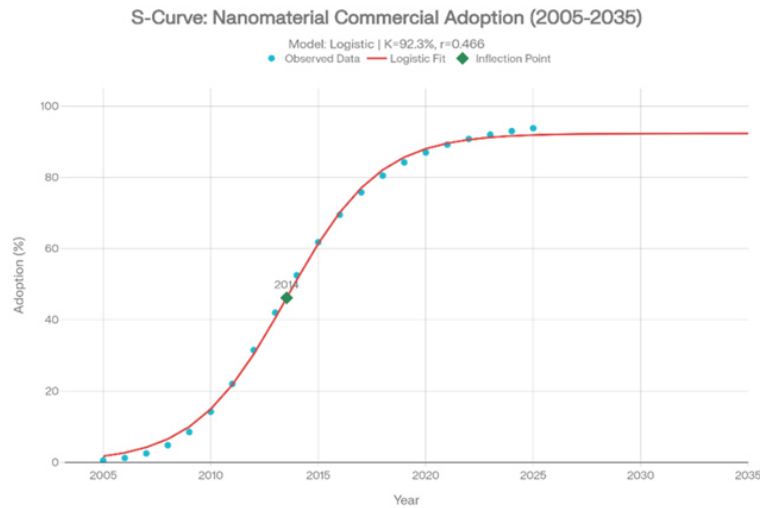


Fig. 1 – Illustrative logistic S-curve model for nanomaterial commercial adoption dynamics (authors' own elaboration based on the theoretical framework of Bengisu and Nekhili, 2006).

3.2. Bibliometric and patent analysis

Bibliometric and scientometric analysis evaluates the scientific production landscape through publication counts, co-citation networks, and keyword co-occurrence mapping, allowing early detection of emerging research directions and correlation of publication activity with Technology Readiness Levels (Lezama-Nicolás *et al.*, 2018). In nanotechnology domains, bibliometric mapping has successfully identified emergent subfields such as 2D materials, guiding R&D investment priorities.

Patent landscape analysis complements bibliometrics by reflecting applied innovation activity and the strategic interests of industrial actors (Huang *et al.*, 2022). Patent landscaping maps the technological domain, identifies dominant organizations and geographic concentrations, and signals technologies approaching commercial readiness or at risk of the 'valley of death' (van Rijn and Timmis, 2023). Key indicators include new patent counts, citation patterns, and inter-entity cooperation networks. Important limitations include registration delays, strategic over- or under-representation of domains, and failure to capture informal or unpatented innovation.

Figure 2 illustrates the evolution of granted nanotechnology patents at USPTO over the 2010-2025 period, demonstrating a transition from exponential growth (2010-2016) to a more linear regime (2017-2025). The inflection suggests market maturation and consolidation in dominant application domains such as nanoelectronics and drug delivery systems, consistent with S-curve diffusion theory.

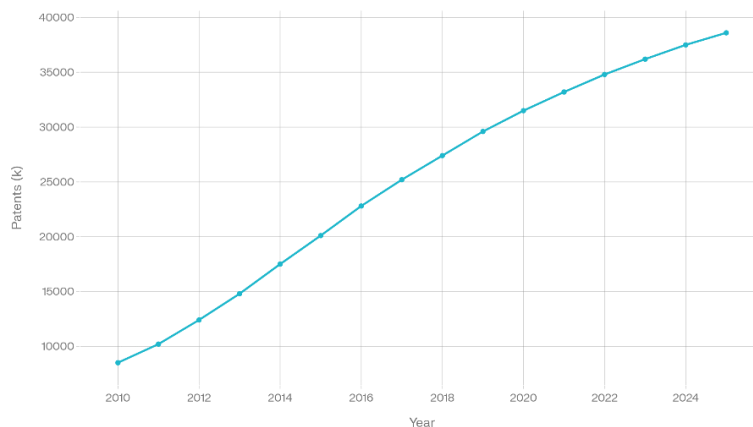


Fig. 2 – USPTO nanotechnology patent trends, 2010-2025 (data source: USPTO Open Data Portal, accessed May 2026).

4. Qualitative forecasting methods

4.1. The Delphi method

The Delphi method achieves structured expert consensus through iterative anonymous questionnaire rounds, statistical feedback aggregation, and successive opinion revision (Linstone and Turoff, 1975). Anonymity reduces hierarchical influence and group conformity, improving the independence of individual judgments. In micro and nanotechnology forecasting, Delphi is widely applied for identifying emerging research directions, estimating technology maturity horizons, and evaluating feasibility barriers to industrial adoption (Mufti *et al.*, 2023). Real-time Delphi variants using digital platforms accelerate the process and increase iteration counts.

Limitations include dependence on expert selection quality, risk of cognitive biases (confirmation bias, anchoring, overconfidence), and a tendency toward consensus that may suppress disruptive or non-linear scenario exploration (Khodyakov *et al.*, 2023). Contemporary literature recommends integrating Delphi within hybrid frameworks, correlated with bibliometric or patent data, to improve forecast robustness.

4.2. Scenario planning and strategic roadmapping

Prospective scenario planning constructs coherent sets of alternative futures, distinguishing exploratory scenarios - investigating possible trajectories from current dynamics - from normative scenarios, which analyze pathways toward a desired strategic state (Schoemaker, 1995; Ringland, 2014). Scenarios are especially valuable for managing radical uncertainty in nanotechnology domains, where regulatory impacts and societal acceptance factors cannot be modeled quantitatively. Their primary limitation is speculative risk when not grounded in rigorous data analysis.

Strategic roadmapping connects future technological vision to present resource allocation decisions through multi-level planning frameworks integrating the strategic, resource, and market dimensions (Phaal and Muller, 2009). Technology roadmaps are extensively used in microelectronics - notably the IEEE IRDS - and in nanomaterial R&D planning. Limitations include rigidity when not periodically updated and over-structuring that constrains disruptive alternative exploration (Phaal *et al.*, 2004).

5. Hybrid approaches and artificial intelligence integration

Contemporary literature converges on the view that single-method forecasting is insufficient for complex, volatile technology domains. Quantitative methods are objective but retrospective; qualitative methods are flexible but subjective. Methodological fragmentation is identified as a primary cause of strategic forecasting failures in convergent technology domains (Bengisu & Nekhili, 2006). To structure the complex integration of these diverse inputs, hybrid frameworks frequently employ multi-criteria decision-making (MCDM) methods, such as the Analytic Hierarchy Process (AHP). AHP allows decision-makers to systematically weigh quantitative patent data against qualitative expert scenarios (Saaty, 1980).

To illustrate this approach, an illustrative pairwise comparison matrix was constructed by the authors, evaluating four criteria: accuracy, cost, complexity, and data needs. The assigned values reflect the relative importance of each criterion in strategic foresight contexts. Table 2 presents the resulting matrix.

Table 2

AHP pairwise comparison matrix for forecasting method selection criteria

Criteria	Accuracy	Cost	Complexity
<i>Accuracy</i>	1.00	3.00	5.00
<i>Cost</i>	0.33	1.00	2.00
<i>Complexity</i>	0.20	0.50	1.00
<i>Data needs</i>	0.50	2.00	3.00

The normalized priority weights derived from Table 2 are visualized in Figure 3, yielding values of 48.2%, 15.8%, 8.8%, and 27.2% respectively. The consistency ratio $CR=0.005$, well below the accepted threshold of 0.10 (Saaty, 1980), confirms matrix coherence, indicating that forecast accuracy and data availability are prioritized over implementation cost and model complexity.

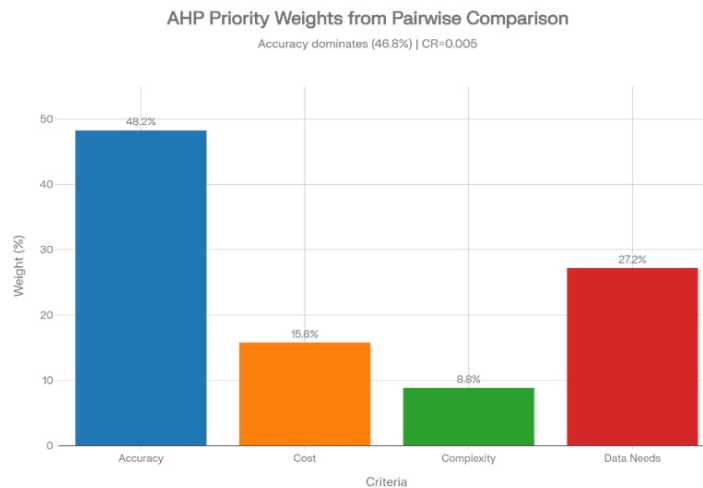


Fig. 3 – Illustrative AHP priority weights for forecasting method selection criteria (authors' own elaboration, based on Saaty, 1980).

Effective hybrid integration combines bibliometrics and patent analysis with Delphi or scenario methods to achieve cross-validation and mutual enrichment. Bibliometric results identify empirical trends that Delphi panels can interpret and project strategically; expert foresight in turn guides updated bibliometric indicator selection. Patent data combined with scenario planning contextualizes innovation activity against regulatory and market dynamics (Huang *et al.*, 2022). The integration logic is iterative and reflexive - quantitative outputs inform qualitative hypotheses, which guide subsequent quantitative analyses.

Artificial intelligence substantially extends hybrid forecasting capacity. Machine learning models process large heterogeneous datasets with greater flexibility than parametric models (Krestel *et al.*, 2025; Fildes and Goodwin, 2007). NLP techniques - Latent Dirichlet Allocation, word embeddings, and transformer-based models such as PatentBERT - enable automated extraction of emerging themes from literature and patent corpora (Krestel *et al.*, 2025). Graph neural networks facilitate analysis of technology convergence and systemic interdependencies (Krestel *et al.*, 2025). Critical limitations include model opacity, risk of amplifying training data biases, and difficulty of real-world decision-context validation (Daim *et al.*, 2006).

6. Case study: Strategic forecasting of electromagnetically assisted microwave pasteurization

As an illustrative application for strategic forecasting methods in micro and nanotechnologies, the field of microwave processing technologies can be analyzed, with a focus on electromagnetically assisted pasteurization. This technology is relevant because it combines food engineering, high-frequency electromagnetic fields, functionalized micro and nanomaterials, miniaturized sensors and modern process control systems.

Conventional pasteurization aims to reduce microbial load and extend the shelf life of food products, but classical heating methods can have limitations such as slow heat transfer, high energy consumption and the impact of some sensory or nutritional properties. In contrast, microwave processing allows for volumetric heating, through the direct interaction between the electromagnetic field and polarizable molecules in the product. Thus, energy can be generated inside the material, not just transferred from the surface to the center, which can reduce processing time and improve energy efficiency (Chandrasekaran *et al.*, 2013).

The link with micro and nanotechnologies occurs through the use of materials and systems capable of more precisely controlling the interaction between microwaves and the food product. Functionalized micro and nanomaterials, nanocomposites, active packaging or miniaturized sensors can contribute to uniform heating, temperature monitoring, control of dielectric properties and process optimization. For example, integrated sensors can track parameters such as temperature, humidity or dielectric changes in real time, and functionalized materials can contribute to more efficient distribution of electromagnetic energy (Regier *et al.*, 2017).

Table 3 presents the technological elements relevant to the case study.

Table 3
Technological elements relevant to the case study

Analyzed element	Role in assisted pasteurization	Relevance for strategic forecasting
<i>High frequency electromagnetic field</i>	<i>Produces volumetric heating of the food product</i>	<i>Determine process efficiency and scaling limits</i>
<i>Dielectric properties of food</i>	<i>Influences the absorption of electromagnetic energy</i>	<i>Required for modeling and process optimization</i>
<i>Functionalized micro and nanomaterials</i>	<i>They can help control energy absorption and distribution</i>	<i>Indicates emerging directions of innovation</i>
<i>Miniaturized sensors</i>	<i>Monitors temperature, humidity or other parameters</i>	<i>Allow real-time control and reduce technological risks</i>

Analyzed element	Role in assisted pasteurization	Relevance for strategic forecasting
<i>Active/smart packaging</i>	<i>They can interact with the microwave in a controlled manner or monitor the product</i>	<i>Create new applications in the food industry</i>
<i>Electromagnetic modeling</i>	<i>Simulates field and temperature distribution</i>	<i>Reduces experimental costs and supports design</i>
<i>Automated control systems</i>	<i>Adjust processing parameters in real time</i>	<i>Support integration into smart industrial processes</i>

From a strategic forecasting perspective, electromagnetically assisted pasteurization is an example of an emerging technology whose evolution is difficult to predict using traditional methods alone. Its development depends simultaneously on experimental results, progress in microwave equipment, food safety regulations, consumer acceptance, and the maturation of micro and nanomaterials used in direct or indirect contact with food. Therefore, the strategic analysis must integrate multiple sources of information: experimental data, patent trends, scientific publications, and expert opinions (Sorrentino *et al.*, 2007).

Table 4 presents strategic forecasting methods applicable to the case study.

Table 4
Strategic forecasting methods applicable to the case study

Method	Application in the case study	Expected result
<i>Analysis of technological trends</i>	<i>Identifying developments in microwave processing, sensors and nanomaterials</i>	<i>Establishing major development directions</i>
<i>Analysis of scientific publications</i>	<i>Tracking research intensity in microwave pasteurization and functionalized materials</i>	<i>Identifying areas of high academic interest</i>
<i>Patent analysis</i>	<i>Observation of industrially protected solutions and active actors</i>	<i>Estimating marketing potential</i>
<i>Delphi method</i>	<i>Consulting experts in food engineering, microwaves, nanomaterials and regulation</i>	<i>Validating hypotheses and identifying barriers</i>
<i>Prospective scenarios</i>	<i>Building alternative evolution options</i>	<i>Anticipating risks and opportunities</i>
<i>Technological roadmapping</i>	<i>Correlating objectives with time horizons</i>	<i>Establishing technological development stages</i>

In such a case study, experimental data are needed to assess the dielectric properties of food, temperature distribution, microbial inactivation efficiency and impact on product quality. Patent analysis can highlight areas of industrial interest, such as microwave pasteurization equipment, microwave-compatible packaging, integrated sensors and electromagnetic field control methods. The Delphi method, based on expert consultation, can be used to estimate technological maturity, identify implementation barriers and determine the applications with the greatest potential (Duncan, 2011).

A SWOT analysis for electromagnetically assisted pasteurization is presented in Table 5.

Table 5
SWOT analysis for electromagnetically assisted pasteurization

SWOT component	Relevant elements
<i>Strengths</i>	<i>Volumetric heating, reduced processing time, potential for energy efficiency, possible better preservation of food quality</i>
<i>Weaknesses</i>	<i>Risk of uneven heating, high equipment costs, scaling difficulties, need for precise process control</i>
<i>Opportunities</i>	<i>Smart food industry, active packaging, integrated sensors, Industry 4.0 technologies, products with extended shelf life</i>
<i>Threats</i>	<i>Strict food safety regulations, uncertainties regarding nanomaterials, limited consumer acceptance, competition from alternative technologies</i>

In the short term, the evolution of this technology involves experimental validation of processes, dielectric characterization of food products and assessment of the safety of the materials used. In the medium term, the main direction may be the development of pilot prototypes, sensor integration and testing under industrial conditions. In the long term, electromagnetically assisted pasteurization could become part of intelligent food processing lines, integrated into Industry 4.0 concepts, with real-time monitoring and automated control of process parameters (Porter and Cunningham, 2011).

In conclusion, electromagnetically assisted microwave pasteurization represents a suitable case study for a paper on strategic forecasting methods for micro and nanotechnologies. It demonstrates how the convergence of high-frequency electromagnetic fields, functionalized micro and nanomaterials and intelligent monitoring systems can generate new technological trajectories. Strategic forecasting allows the identification of opportunities, risks and steps necessary for the transfer of this technology from the laboratory to safe and efficient industrial applications.

7. Critical analysis and research gaps

The systematic literature review reveals three major research gaps constraining forecasting effectiveness in micro and nanotechnology domains.

First, methodological fragmentation remains pervasive. Quantitative and qualitative methods are predominantly applied in isolation, producing partial results that fail to capture simultaneous dynamics of technology, market, and regulatory dimensions (Bengisu and Nekhili, 2006). Few validated frameworks enable systematic integration of bibliometric data, patent indicators, mathematical modeling, and expert opinion within a unified process.

Second, existing models are predominantly descriptive and retrospective, oriented toward explaining past events rather than supporting proactive strategic decisions. The literature identifies a clear deficit of decision-oriented forecasting frameworks that embed anticipatory reasoning directly into resource allocation and R&D prioritization processes (Cuhls, 2003).

Third, available models are largely inadequate for convergent and emergent technologies. Classical approaches assume relatively stable evolutionary patterns incompatible with the non-linear dynamics and interdisciplinary convergence characteristic of nanotechnologies (Waldrop, 2016; Phaal *et al.*, 2004). The post-Moore era and convergence of nanomaterials, AI, and biotechnology demand genuinely adaptive multi-level frameworks that can be iteratively recalibrated as new data emerges.

These gaps collectively justify the development of a novel integrated methodological framework, capable of combining quantitative rigor, expert foresight, and AI-based analytical tools into a robust, empirically validated decision-support system for emerging technology domains.

8. Conclusions

Strategic forecasting for emerging technologies in micro and nanotechnologies requires a fundamentally integrated approach, as demonstrated by the case study on electromagnetically assisted microwave pasteurization. Quantitative methods-time series analysis, S-curve modeling, and patent/bibliometric analysis-provide objective, measurable indicators of technological maturity but remain retrospective and inadequate for capturing disruptive innovations. Qualitative methods-the Delphi approach, scenario planning, and roadmapping-handle radical uncertainty and integrate expert knowledge effectively, yet are constrained by cognitive biases and limited standardization. The case study exemplifies how convergent technologies, spanning food engineering, electromagnetic fields, micro and nanomaterials, sensors, and intelligent process control, demand hybrid frameworks that transcend traditional disciplinary boundaries.

Methodological fragmentation remains the primary obstacle to effective strategic forecasting in these domains. The integration of bibliometric rigor, patent intelligence, expert foresight, and AI-enhanced analytics—as illustrated through the case study's multi-dimensional assessment—enables cross-validation and mutual reinforcement of forecasting outputs. Contemporary hybrid approaches augmented by machine learning and natural language processing offer the most promising direction, though their implementation remains inconsistent and insufficiently validated across diverse technology sectors.

The case study validates the research gaps identified in this paper: fragmented methodologies fail to capture simultaneous technology, market, and regulatory dimensions; existing models emphasize descriptive retrospection rather than proactive decision support; and classical frameworks prove inadequate for non-linear, convergent innovation patterns. These interconnected gaps justify the development of an integrated, adaptive strategic forecasting framework specifically designed for the complexity of emerging micro and nanotechnology domains. Such a framework must combine quantitative rigor, qualitative foresight, and AI-based analytical tools to provide a coherent, empirically validated instrument for research and innovation decision-making in the laboratory-to-market transition phase—precisely where electromagnetically assisted pasteurization and similar convergent technologies require robust anticipatory guidance.

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METODE DE PROGNOZĂ STRATEGICĂ PENTRU MICRO ȘI NANOTEHNOLOGII

(Rezumat)

Proгноza strategică este esențială pentru procesul decizional în economia bazată pe cunoaștere, unde ritmul rapid al schimbărilor tehnologice impune o anticipare structurată. Această lucrare analizează critic principalele metode de prognoză utilizate în domeniul micro și nanotehnologiilor și le evaluează bazele teoretice, punctele tari și limitările.

O analiză sistematică a literaturii de specialitate acoperă abordările cantitative - inclusiv extrapolarea seriilor temporale, modelele de difuzie de tip curbă S, analiza bibliometrică și analiza peisajului brevetelor -, precum și metodele calitative, cum ar fi tehnica Delphi, planificarea scenariilor, roadmaping-ul strategic și judecata experților. De asemenea, sunt examinate cadrele hibride și cele optimizate prin inteligență artificială.

Analiza demonstrează că metodele cantitative sunt obiective, dar predominant retrospective, în timp ce metodele calitative sunt flexibile, însă vulnerabile la erori de judecată (biases) și la o validare limitată. Abordările hibride par a fi cele mai promițătoare, deși implementarea lor rămâne neuniformă. Deficiențele metodologice identificate justifică dezvoltarea unui cadru de prognoză integrat și adaptiv pentru tehnologiile emergente.