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Artificial intelligence assistance in foresight research: Enhancing technology assessment through data-driven methods

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ABSTRACT

Foresight can be viewed as an approach to managing uncertainty – an instrument that enables foreseeing while actively shaping the future under conditions of unpredictability. The rapid development of artificial intelligence (AI) has introduced new opportunities for foresight research. Although the AI methods have not traditionally been part of the foresight canon, they offer significant potential for future applications. Integrating machine learning (ML) techniques into foresight research appears to be a natural progression. AI provides transformative capabilities by analysing complex datasets, uncovering hidden relationships, and generating data-driven recommendations. This work investigated the integration of AI tools into technology foresight projects by reviewing the existing literature on their combined application. The analysis identifies the most frequently used AI and foresight methods, along with their primary objectives, providing a structured overview of current practices. Empirical analysis, based on the data from a technology foresight project, demonstrates how AI can be utilised to enhance data analysis, thereby supporting theoretical considerations and complementing the traditional expert panel approach for technology clustering. The AI-assisted process provides a scalable alternative to traditional methods, with code tools, enhancing the perspectives on identifying technology clusters, selecting key attributes, and incorporating expert self-assessment. However, the value of the proposed approaches lies more in a posteriori analysis, which can be utilised in future foresight projects regarding the attributes used for evaluation or the selection of expert panels. The diversity of the proposed analyses demonstrates various interpretation possibilities but does not fundamentally influence the achievement of the main goal, which is the identification of key technologies.

Keywords: foresight, artificial intelligence, large language models, clustering, biclustering, technology, assessment, decision support.

INTRODUCTION

The term "technology" originates from the Greek word τέχνη [techné], meaning art, science, craft, skill, or cunning. The suffix -logy (from the Greek λόγος [logós]) indicates a semantic connection with speech, knowledge, or theory [1,2]. In the literature, numerous attempts have been made to systematise the explanations of the term within the literature, both in its general meaning [3,4] as well as within specific domains, such as, e.g. health [5], production [6,7], or level of advancement, e.g., emerging [8]. In its broadest sense, as defined by OECD [9] and initially formulated by Griliches [10], technology is conceived as a body of knowledge concerning the methods for transforming resources into desired outputs. It encompasses the practical application and integration of technical methods, systems, tools, skills, and procedures within business processes or products.

Technologies play a crucial and transformative role in the development of societies, economies, and the shaping of the future of civilisation [11]. Their importance in contemporary society, where increasingly complex challenges are encountered, is undeniable, with their influence becoming more visible and essential across all areas of life [12]. As a result of recognising the role of technology, as well as the need to direct and control technological development, a variety of methods, models, and tools for its analysis and evaluation have been developed. These methods have been evolving since the 1960s, although it is the Fourth Industrial Revolution that has significantly increased their importance due to the complexity of technological systems, their interconnections, and their constant evolution. The set of methods that can be used in the process of technology assessment includes both approaches adapted from other fields and those specifically designed for technology evaluation. One of the method typologies in the literature within the context of foresight is the "foresight diamond" developed by R. Popper [13]. The identified methods were categorised as quantitative, qualitative, mixed, as well as according to the type and source of knowledge on which they are based: derived from creativity, based on imagination or evidence, resulting from personal experience, or emerging through interaction. A fundamental classification was also proposed by Popper and Korte [14], dividing methods into two groups: "hard" methods, which utilise statistical and quantitative tools, and "soft" methods. A proposal by Stirling et al. [15], dedicated to assessment in the context of sustainable development, introduced a two-dimensional typology: opening/closing methods and broad/narrow methods, with an additional distinction between participatory-deliberative and expert-analytical approaches. Among the tools used to identify the key drivers of technological change and understand their interdependencies, structural analysis has gained prominence [16], offering a systematic approach to mapping and analysing the relationships between various influencing factors. Although the range of potential technology analysis methods is vast, the set of methods most frequently employed has remained remarkably consistent over the years and include: morphological analysis, SWOT analysis, multi-criteria analysis, cross-impact/structural analysis, bibliometrics, brainstorming, relevance trees, trend extrapolation/megatrends, essays, gaming, key technologies, stakeholder mapping, technology roadmapping, Delphi, modelling and simulation, expert panels, citizen panels, backcasting, literature review, scenarios, environmental scanning, questionnaire/survey, workshops, and interviews [17–20].

The objective of this study was to demonstrate, based on a literature review and experiments, the role and potential applications of AI assistance in foresight projects. Within the field of technology management, foresight is regarded as a forward-looking process that systematically attempts to anticipate and shape the future of science, technology, economy, and society. As defined by B. Martin [21], foresight is "the process involved in systematically attempting to look into the longer-term future of science, technology, the economy and society with the aim of identifying the areas of strategic research and the emerging generic technologies likely to yield the greatest economic and social benefits." Alongside foresight, other approaches such as technology assessment (TA) and technology forecasting (TF) coexist and are actively used in the field of technology management. While TA primarily evaluates the impacts and implications of existing or emerging technologies, and TF focuses on predicting future technological trends, foresight emphasises a broader, more strategic perspective toward shaping desirable scenarios.

Foresight, while valuable in anticipating the future, can be costly, time-consuming, and prone to errors when obtained through traditional methods, as it relies on subjective expert assessments and long-term forecasts that can quickly become outdated [22]. Inaccuracies in the initial input may lead to flawed or non-representative scenarios, potentially affecting subsequent decision-making [23]. Moreover, in the face of rapid technological and societal changes, its results often become irrelevant, and the process is at risk of inaccurate predictions. AI can address these issues by offering faster, more objective, and flexible analyses. Integrating machine learning with foresight methodologies – such as scenario planning, horizon scanning, the Delphi method, and trend analysis – enhances decision-making accuracy, supports risk anticipation, and improves organisational adaptability [24]. AI enables automated data analysis, pattern recognition, predictive modelling, and dynamic scenario generation, enhancing the accuracy as well as resilience of technology evaluation processes, particularly in complex and rapidly evolving environments [25]. The application of dedicated AI models in various embedded systems is emerging as a particularly promising direction, offering new possibilities for real-time data processing, intelligent automation, and adaptive system behaviour in increasingly complex technological environments [26]. Fuzzy hybrid methodologies facilitate foresight to mitigate uncertainty and promote strategic innovation processes [27]. Addressing future challenges requires a focus on efficient resource use and the integration of responsible innovation to ensure sustainable and socially aligned technological development [28]. Recent literature discusses the emergence of a new generation of foresight that focuses on emerging technologies of Industry 4.0 and the co-creation of future scenarios by futurists, utilising the insights derived from big data [29]. Combining expert participation with artificial AI capabilities in a hybrid approach opens new perspectives for forecasting [30]. In particular, the broader availability of natural language processing (NLP) tools, such as ChatGPT, Copilot, and Gemini, has opened up new opportunities for both foresight practitioners and researchers [31,32]. Supports the creation of targeted projects, policies, and strategies by guiding decision-makers in prioritising actions, optimising resource use, and aligning innovations with societal and market demands [33].

This study contributes by offering a comprehensive review of the current literature on the application of artificial intelligence in foresight projects and by illustrating the practical potential of AI-based data analysis using the empirical data from a real foresight initiative. The findings highlight how generative AI (GenAI) assistance supports expert judgment, uncovers hidden patterns, and increases the robustness of foresight analyses. The research process is illustrated in Figure 1. Considering the two types – human-driven foresight as well as AI- and ML-driven foresight [34], the article incorporated AI into human-driven processes to make the foresight process more efficient and reflective of diverse perspectives. The literature review addressed the research questions: Q1. Which AI methods most frequently co-occurred with specific foresight methods in the analysed publications? The second part of the study illustrates the supervised AI-assisted process of data analysis and addresses Q2. In what ways can AI facilitate expert-based technology foresight?

The structure of this paper is as follows: the next section provides a review of AI in technology foresight projects with the help of large language models (LLMs). It then explores the practical application of AI-based methods for technology analysis within the NT FOR Podlaskie 2020 project. The paper concludes with a discussion of the findings.

AI IN FORESIGHT PROJECTS

To identify relevant studies at the intersection of foresight and AI, a systematic search was conducted using Scopus, IEEE Xplore, and Web

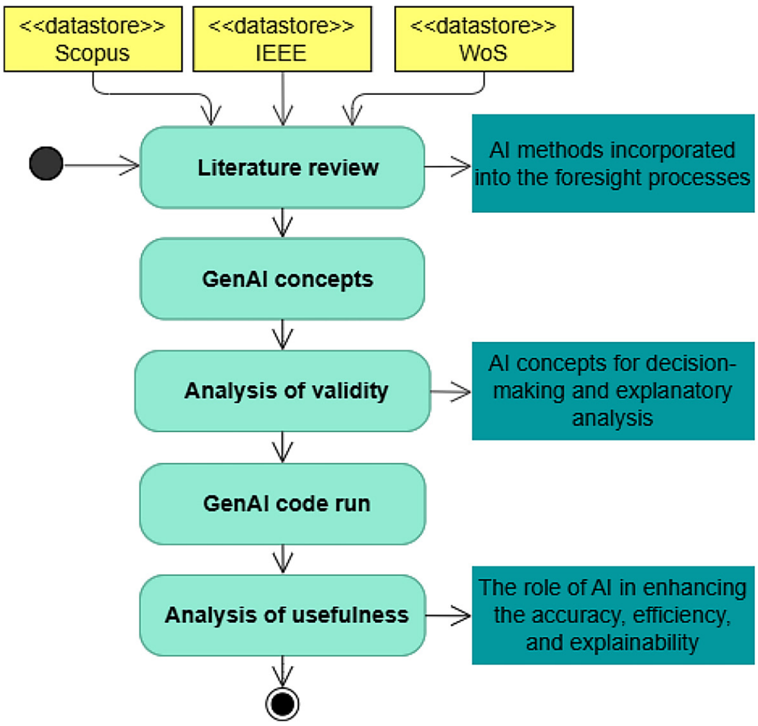

Figure 1. UML diagram of the study flow

of Science databases. The search query targeted the documents containing the term “foresight” in combination with a wide array of AI-related terms (e.g., artificial intelligence, machine learning, deep learning, neural networks, natural language processing, large language models, etc.) within titles, abstracts, or keywords (Table 1). The publication window was limited to the years 2017–2025 (until May 15th), as the period marks a significant acceleration in the development and application of AI techniques, particularly following the publication of the conference paper “Attention Is All You Need” by Vaswani et al. (2017) [35], which introduced the transformer architecture. This breakthrough laid the foundation for many modern AI applications, especially in natural language processing (NLP) and large language models (LLMs), which are increasingly used in foresight research, both as tools for analysis and as objects of investigation.

Foresight-related keywords were included specifically in the title field to ensure that the selected papers genuinely addressed foresight, rather than simply referencing the term in passing. Following the removal of duplicates, a total of 259 unique records remained – all sourced from Scopus, as IEEE Explore and Web of Science did not contribute any additional unique entries.

In the context of this literature survey on AI support for foresight projects, the review of the analysed publications reveals that the topic areas addressed are predominantly technology-related in various ways. Although some publications discussed broader issues such as societal dynamics, policy development, or strategic planning, these discussions were often framed in the context of technological change, digital transformation, or innovation management.

A formal investigation of the areas conducted using embedding technology highlights the following sectors: agriculture and sustainability, education and digital skills, economics and public policy, health and medicine, energy and environment, and innovation and general foresight (Figure 2). Analysis of the results reveals that artificial intelligence is not only a tool, but also a subject of foresight research itself [36], including studies that incorporate AI-based methods [37]. AI is widely recognised as a key driver of transformation and one of the most prominent topics in strategic foresight initiatives across various industries [38]. Furthermore, AI competences have been anticipated through ICT-focused foresight initiatives, which aim to address the digital and AI skills gap in response to the ongoing technological advancements [39].

Hybrid models effectively address the challenge of integrating the strengths of various modelling approaches. They reduce uncertainty by clarifying ambiguous value judgments in later visualisations and assist in pinpointing potential actions after future scenarios have been established,

Table 1. Search queries and the number of articles

Database	Search query	Number of documents
Scopus	(TITLE („foresight”) OR KEY („foresight”)) AND TITLE-ABS-KEY-AUTH („artificial intelligence” OR ai OR „machine learning” OR ml OR „deep learning” OR „neural networks” OR „neural network” OR ann OR rnn OR cnn OR lstm OR „natural language processing” OR nlp OR „text mining” OR „data mining” OR „predictive modeling” OR „AI-based methods” OR „genetic algorithms” OR „evolutionary algorithms” OR „swarm intelligence” OR „reinforcement learning” OR „support vector machines” OR svm OR „fuzzy logic” OR „decision trees” OR „random forest” OR „bayesian networks” OR „deep neural networks” OR „transformer models” OR „large language models” OR llm OR „knowledge graphs”) AND PUBYEAR > 2016 AND PUBYEAR < 2026 AND (LIMIT-TO (LANGUAGE , „English”))	259
IEEE Xplore	((„Document Title”:”foresight” OR „Index Terms”:”foresight”) AND („All Metadata”:”artificial intelligence” OR „All Metadata”:AI OR „All Metadata”:”machine learning” OR „All Metadata”:”deep learning” OR „All Metadata”:”neural networks” OR „All Metadata”:”natural language processing” OR „All Metadata”:”genetic algorithms” OR „All Metadata”:”reinforcement learning” OR „All Metadata”:”decision trees” OR „All Metadata”:”random forest” OR „All Metadata”:”transformer models”))AND (Publication Year:2017 TO 2025) AND (Language:English)	36
Web of Science	((TI=(foresight) OR AK=(foresight)) AND TS=(„artificial intelligence” OR „ai” OR „machine learning” OR „ml” OR „deep learning” OR „neural networks” OR „neural network” OR „ann” OR „rnn” OR „cnn” OR „lstm” OR „natural language processing” OR „nlp” OR „text mining” OR „data mining” OR „predictive modeling” OR „AI-based methods” OR „genetic algorithms” OR „evolutionary algorithms” OR „swarm intelligence” OR „reinforcement learning” OR „support vector machines” OR „svm” OR „fuzzy logic” OR „decision trees” OR „random forest” OR „bayesian networks” OR „deep neural networks” OR „transformer models” OR „large language models” OR „llm” OR „knowledge graphs”))AND PY=(2017-2025) AND LA=(English)	157

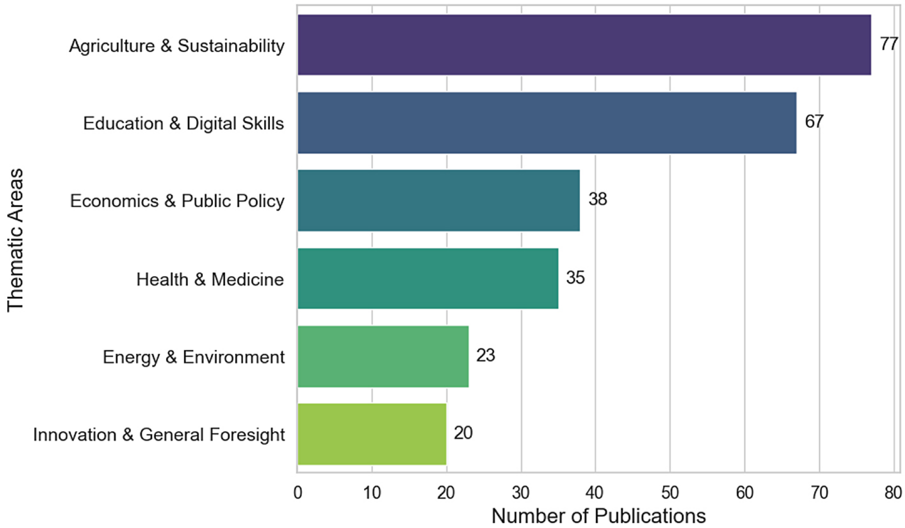

Figure 2. Distribution of AI-supported foresight applications across thematic areas

enhancing the ability to connect with the most beneficial future [40]. To identify patterns in the combined use of AI and foresight methods, a co-occurrence analysis was conducted based on the titles, abstracts, and keywords across the selected dataset. This enabled the mapping of how specific AI techniques are applied in conjunction with foresight approaches in published articles (Figure 3).

A co-occurrence analysis of foresight methods and AI techniques shows that approaches such as scenario analysis, trend analysis, bibliometrics, Delphi, SWOT, and brainstorming are often combined with AI methods. Among AI techniques, artificial intelligence, machine learning, NLP, text mining, and neural networks are the most frequent. The results highlight the strong link between scenario and trend-based foresight and AI, reflecting the growing role of predictive analytics and text processing in the field. Overall, AI is increasingly used to support scenario building, trend detection, expert knowledge aggregation, and analysis of large textual datasets, often drawn from publications, reports, patents, surveys, and quantitative indicators.

Analysis of keyword usage across the dataset reveals a notable preference among authors for the general term “artificial intelligence”, which appears significantly more frequently than more specific terms, such as “machine learning” or “deep learning.” Interestingly, “neural networks” also show relatively high occurrence, despite being a subset of machine learning and deep learning. This suggests that while authors often refer to AI in broad terms, they may also highlight specific technologies, such as neural networks, when relevant, potentially overlooking the hierarchical structure of AI terminology. Such patterns indicate a conceptual gap in how AI methods are referenced in foresight-related literature, which may affect the clarity and precision of methodological reporting. When recognising the frequent imprecision in method definitions across scientific articles, it is evident that AI-assisted text/speech analyses, often supported by LLMs, are increasingly being incorporated into foresight processes, both as analytical tools and as sources of scenario generation. Alongside these LLM-driven qualitative insights, several studies proposed quantitative enhancements, such as fuzzy numbers and mathematical models, to improve precision in decision-making processes, including Delphi surveys, e.g., [41].

In light of the summaries made, bibliometric analysis has never been as accessible and efficient as it is today, owing to the integration of AI tools. In the context of predicting the technological future, AI enables the rapid processing of massive amounts of scientific publications, patents, and other textual data, revealing hidden patterns, emerging trends, and strategic insights. This transformation significantly reduces the manual effort traditionally required in bibliometric research, enabling researchers to extract valuable predictive information from complex and distributed data sources. The analysis above was conducted in Python using the code generated with the support of GPT models, such as those integrated in ChatGPT and Copilot.

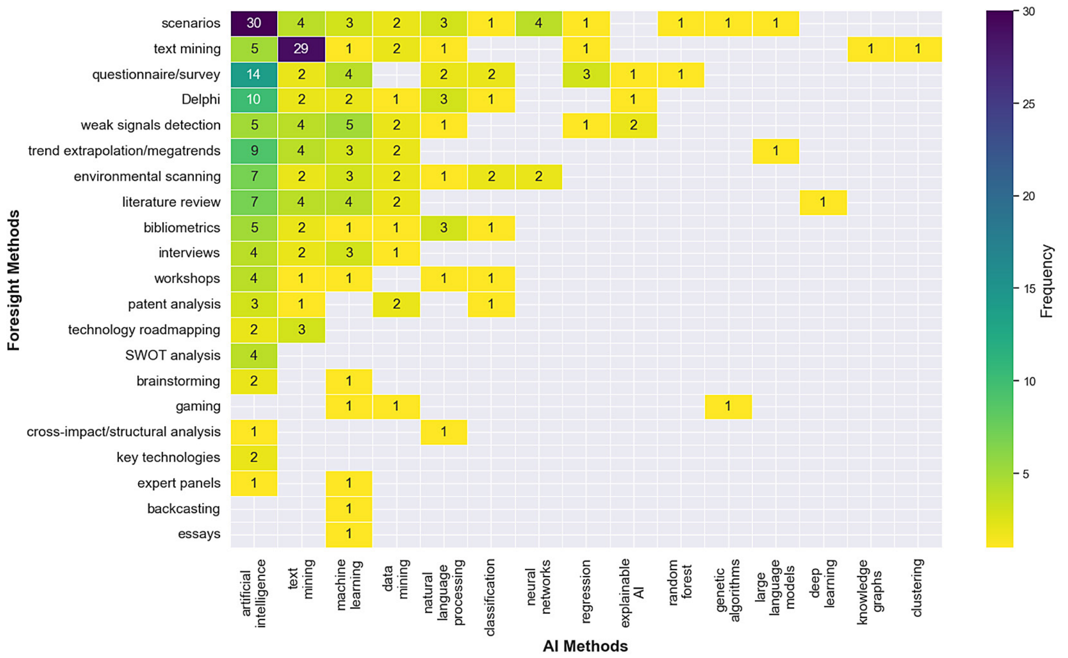

Figure 3. Co-occurrence matrix: AI and traditional foresight methods

CASE STUDY OF THE TECHNOLOGY FORESIGHT PROJECT

To demonstrate the practical application of AI in foresight research, this section provides a case study on assessing and grouping emerging technologies. It combines the AI-driven methods with human validation to offer insights into how generative AI ideas can improve framework design and support decision-making processes. The following subsections present the GenAI concepts for the technology foresight project data, provide a brief introduction to the proposed methods, and present the results, including the clustering of technologies and the similarities between experts, along with a discussion.

Generative AI concepts in the context of technology foresight

Comparison of LLM systems is a frequently discussed topic, and the basis of metrics is, for example, success rates, runtime efficiency, memory usage, and error-handling capabilities [42]. Most formal evaluations of deep learning models have relied heavily on standard academic datasets, which have limitations in accurately reflecting real-world performance [43]. In contemporary research practice, advanced AI tools are increasingly used not only to provide methodological guidance in selecting appropriate analytical techniques but also to support various aspects of complex research, including foresight projects. This paper presents an experimental comparative approach, focusing on the synthesis of generative solutions. This analysis directly addresses research question Q2: In what ways can AI facilitate expert-based technology foresight?

Two leading artificial intelligence systems – ChatGPT 4o and M365 Copilot were prompted with a detailed description of a dataset from the NT FOR Podlaskie 2020 project [44]. The project aimed to develop a desirable socio-economic development scenario for the Podlaskie region in Poland. It focused on nanotechnologies aligned with regional development goals and projecting a regional nanotechnology strategy [2,45]. The main part of the NT FOR was the evaluation of 57 nanotechnologies (T1, T2, …, T57) across 8 domains to select innovation priorities (Appendix 1 and Appendix 2). The analytical methods included calculating an average for the criteria weighed (or not) by the level of expert knowledge, and creating a ranking based on the average.

The project data was used to answer the question about the machine learning or statistical methods that AI tools would suggest for analysing a multidimensional dataset consisting of attractiveness and feasibility assessments, all rated on Likert scales, along with expert knowledge self-assessments. The insights from this experiment provide a comparative view on how generative AI systems can support methodological decision-making in technology foresight research, thereby contributing to answering Q2.

The following prompt was employed: I'm working with a dataset from the NT FOR Podlaskie 2020 project, which evaluated 57 technologies across seven application areas (plus a miscellaneous group) to identify and prioritise innovations for regional development in the Podlaskie region of Poland. Each technology was assessed by 19 experts using 13 attractiveness criteria (e.g., market potential, alignment with regional goals) and 8 feasibility criteria (e.g., resource availability, technical complexity). All scores are on a 1–5 Likert scale. Additionally, each expert provided a self-assessed knowledge level (on a 1–5 scale) for each domain. I do not have a target variable. What machine learning techniques would be appropriate for analysing such data?

The summarised results are presented in Table 2. An unsupervised learning approach was proposed for the application. Notable consistency was observed, and the methods included the conventional statistical techniques. Generative artificial intelligence typically advocates three primary directions of analysis: dimension reduction, clustering, and expert-centred analysis. The received suggestions significantly exceeded the analyses performed in the project. However, the proposed methods are quite standard and do not go beyond the analytical canon and framework. This observation is consistent with the commonly reported assessments in the literature, where the creative capabilities of generative AI, as of 2025, are often described as unexceptional and rather modest in practical applications.

Considering the proposals put by GenAI, variable reduction techniques – such as principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE), uniform manifold approximation and projection (UMAP), factor analysis, latent class analysis (LCA), multidimensional scaling (MDS), and partial least squares (PLS) – play a critical role in uncovering the underlying structure of high-dimensional datasets. These methods enable the identification of latent dimensions or patterns by reducing the complexity of the original variable space, which is particularly valuable in exploratory data analysis, thereby supporting the construction of typologies of technologies, development trajectories, or scenario narratives. However, despite the analytical value of dimensionality reduction, such methods may have limited direct interpretability for decision-makers. Similarly, the recommendation to enrich the analysis with supplementary expert insights – such as those required in multi-criteria decision analysis (MCDA) methods like TOPSIS (technique for order of preference by similarity to ideal solution), AHP (analytic hierarchy process), or preference ranking organisation method for enrichment evaluation (PROMETHEE) – shows limited practical relevance, as these approaches inherently rely on extra expert-defined weights and judgments. In this context, clustering techniques – including k-means, hierarchical clustering, density-based spatial clustering of applications with noise (DBSCAN), Gaussian mixture models (GMMs), biclustering and co-clustering – offer a more actionable framework by organising technologies into discrete and interpretable groups. Considering clustering methods, DBSCAN requires parameter selection, GMMs require the assumption of normal distributions. Clustering and co-clustering (for simultaneous clustering of objects and features) seem particularly useful, allowing for the analysis of the feature matrix as a whole. It provides a different perspective on variables and enables in-depth exploration of local patterns.

This article focused on clustering methods due to their practical utility in identifying homogeneous subsets of technologies or expert judgments, which can guide resource allocation, stakeholder engagement, and the formulation of targeted recommendations. In addition, the study also considers a second analytical dimension: the methods that examine the behaviour and consistency of expert evaluations. While a broad spectrum of techniques exists, the present study employed clustering, correlation and network analysis of expert evaluations. Such approaches are crucial in the context of foresight studies, where expert-based assessments often form the backbone of data collection. Evaluating the internal coherence, reliability, and inter-expert variability not only strengthens the credibility of the results but also helps identify biases, dominant heuristics, or subgroup alignments among experts.

Methodological formulations

This paper employed complementary clustering approaches: (1) hierarchical clustering of technologies; (2) two-dimensional hierarchical clustering of technologies and evaluation

Table 2. AI data analysis proposals

ChatGDP	Copilot
Dimensionality reduction, e.g., principal component analysis (PCA), t-distributed stochastic neighbour embedding (t-SNE), uniform manifold approximation and projection (UMAP)	Dimensionality reduction, e.g. PCA, t-SNE, or UMAP
Clustering, e.g., hierarchical clustering, k-means / k-medoids, Gaussian Mixture Models (GMMs)	Clustering, e.g., k-means or hierarchical clustering, Density-Based Spatial Clustering of Applications with Noise (DBSCAN)
Biclustering or co-clustering	Factor analysis or latent variable models
Multidimensional scaling (MDS)	Weighted Scoring Models
Factor analysis	Multi-criteria decision analysis (MCDA), e.g., TOPSIS, AHP, or PROMETHEE.
Latent class analysis (LCA)	Correlation and network analysis
Association rules or frequent pattern mining	Expert behaviour analysis
Consensus analysis	
Cluster stability and validation	
Multivariate regression or partial least squares (PLS)	

attributes based on aggregated ratings, visualised as clustered heatmaps for attractiveness and feasibility; and (3) spectral co-clustering analysis, which simultaneously identifies coherent groups of technologies and criteria by detecting structural patterns in the data matrix, enabling the discovery of biclusters – subsets of technologies and attributes that exhibit similar behaviour.

Clustering of technologies is based on the matrix of evaluations $X = [x_{ij}]$, where $i = 1, ..., N$ denotes technologies and $j = 1, ..., M$ criteria. In one-dimensional clustering, technologies are grouped into clusters $C = \{C_1, ..., C_p\}$, where P is number of clusters, μ_p is the centroid of cluster C_p . The aim is to minimalize intra-cluster variance:

$$min \sum_{p=1}^{P} \sum_{i \in C_p} \left\| x_i - \mu_p \right\|^2 \tag{1}$$

Two-dimensional clustering assumes that technologies and evaluation criteria were clustered independently, using the same variance-minimisation principle.

Co-clustering (also referred to as biclustering) assumes $C = \{C_1, ..., C_p\}$ as clusters of technologies, $F = \{F_1, ..., F_Q\}$ as clusters of features, μ_{pq} is the mean values in the bicluster (C_p, F_q) and the aim is to minimise within-block variance:

$$min \sum_{p=1}^{P} \sum_{q=1}^{Q} \sum_{i \in C_p} \sum_{j \in F_q} \left(x_{ij} - \mu_{pq} \right)^2 \tag{2}$$

Expert similarity network uses cosine similarity, assumes r_{ui} and r_{vi} are the ratings of experts u and v for technology i:

$$S_{uv} = \frac{\sum_{i=1}^{N} r_{ui} r_{vi}}{\sqrt{\sum_{i=1}^{N} {r_{ui}}^2} \sqrt{\sum_{i=1}^{N} {r_{vi}}^2}} \tag{3}$$

Unsupervised clustering of technologies

In the NT FOR Podlaskie 2020 foresight project, 57 technologies were grouped into four clusters based on the mean scores of attractiveness and feasibility. The resulting groups demonstrated the following characteristics: (1) high attractiveness-high feasibility: priority technologies recommended for immediate investment; (2) high attractiveness-low feasibility: promising technologies that require improvements in implementation potential; (3) low attractiveness – high feasibility: technologies that are easy to implement but offer limited strategic value; (4) low attractiveness-low feasibility: technologies that should be deprioritised or eliminated from strategic focus (Table 3, Figure 4).

By applying methods proposed by GenAI, it becomes possible to view technologies not only through the lens of aggregate scores but also by analysing the individual values of criteria across both attractiveness and feasibility dimensions. This enables a more nuanced and multi-perspective analysis, far beyond simple averaging. In particular, it helps identify the technologies that may appear similar when averaged but differ significantly when examined at the level of individual evaluation criteria. Techniques such as clustering – as recommended by GenAI – allow researchers and decision-makers to identify

Table 3. Traditional clusters by means utilised in NT FOR Podlaskie 2020

Feasibility	High attractiveness	Low attractiveness
High feasibility	T3, T4, T5, T8, T11, T12, T16, T17, T18, T20, T21, T22, T23, T24, T25, T26, T31, T33, T34, T36, T42, T44, T45	T19, T27, T30, T37, T38
Low feasibility	T9, T14, T15, T39, T43	T1, T2, T6, T7, T10, T13, T28, T29, T32, T35, T40, T41, T46, T47, T48, T49, T50, T51, T52, T53, T54, T55, T56, T57

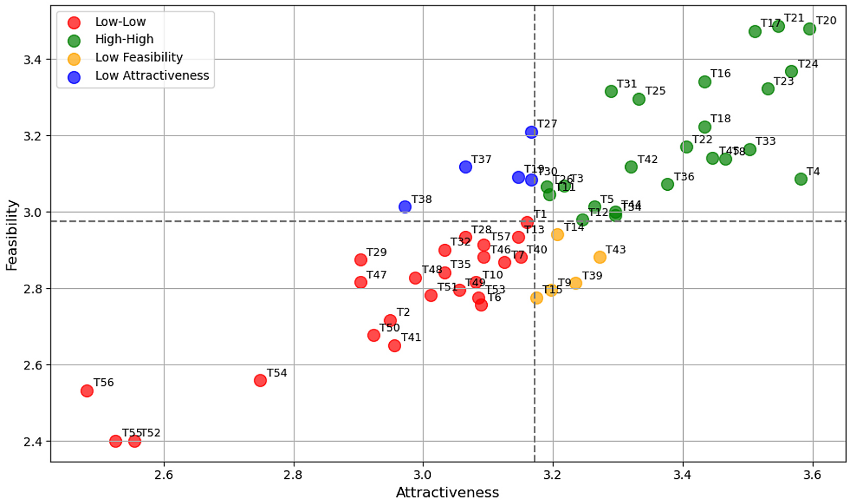

Figure 4. Traditional clusters by means utilised in NT FOR Podlaskie 2020

meaningful groups of technologies, detect latent patterns, as well as develop more targeted and robust strategic recommendations.

Firstly, hierarchical clustering of technologies was applied, with results shown in Figure 5, which represents a more detailed view while still resembling the traditional four-group structure based on averages. The priority technologies identified in the NT FOR project are highlighted in the following groups by marking them with an envelope.

The silhouette score indicated that a three-cluster solution offered the best fit. This finding suggests that although clustering refines group allocation, the overall distribution of technologies remains broadly similar to the original categorisation. Although this grouping highlights the most promising technologies (see Table 4), it does not significantly change the overall distribution from the original results.

Table 5 presents a clustering of two categories of variables: technologies and evaluation criteria. This allows for an assessment of overall similarity patterns across both dimensions. In other words, it groups technologies not only by their attractiveness and feasibility ratings, but also by how they align with specific evaluation criteria. The corresponding dendrogram heatmaps are shown in Figure 6, providing a visual representation of the clustering results. Technologies are grouped based on the similarity of their scores across the evaluation criteria (A1–A13 for attractiveness and F1–F8 for feasibility). Independently, the criteria themselves are also clustered based on how similarly they are rated across technologies. The clustering of evaluation criteria enabled the identification of thematic groups of attributes, which were interpreted and labelled based on their descriptions. The full list of attribute names and descriptions used for interpretation is provided in Appendix 2.

Co-clustering is a simultaneous two-dimensional clustering of technologies and features. Unlike sequential clustering, co-clustering integrates both dimensions in a single analytical step, enabling a deeper understanding of the relationships between technologies and their underlying attributes. As a result, coherent clusters of technologies and features emerge – these are presented in Table 6 and visualised in the heatmaps shown in Figures 7 and 8.

Clustering algorithms are essential tools in data science, particularly useful for exploring and organising complex, multidimensional

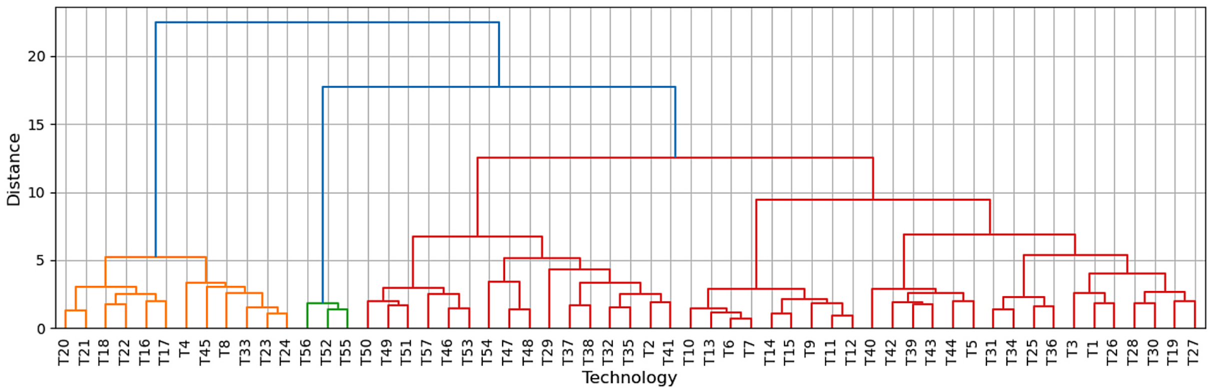

Figure 5. Hierarchical clustering of technologies (Ward method)

Table 4. Hierarchical clustering of technologies

Cluster	Technology
High feasibility and attractiveness ratings – the most strategic, ready for implementation.	T4, T8, T16, T17, T18, T20, T21, T22, T23, T24, T33, T45
Average ratings, moderately attractive and feasible, require further contextual analysis and potential development investments	T1, T2, T3, T5, T6, T7, T9, T10, T11, T12, T13, T14, T15, T19, T25, T26, T27, T28, T29, T30, T31, T32, T34, T35, T36, T37, T38, T39, T40, T41, T42, T43, T44, T46, T47, T48, T49, T50, T51, T53, T54, T57
Low scores in all criteria – few prospects, low readiness for implementation	T52, T55, T56

datasets. In technology assessment, they help identify the groups of technologies with similar levels of attractiveness and feasibility, enabling a more structured and nuanced approach to prioritisation. Importantly, these methods enable decision-makers to analyse the dataset from various analytical perspectives, thereby ensuring that strategic decisions are not predicated solely on aggregated averages. However, clustering results should be treated not as absolute prescriptions, but as supportive guidelines for informed decision-making. Attention to cluster stability and validation is key to ensuring robust and interpretable outcomes. When applied with awareness of their assumptions and limitations, clustering methods enhance the credibility of the

Table 5. Clustered technologies and thematic attribute groups for attractiveness and feasibility dimensions

Cluster	Technology	Cluster	Features
Attractiveness			
Technologies with the highest attractiveness	T4, T8, T16, T17, T18, T20, T21, T22, T23, T24, T33, T45	Implementation potential	A2, A8, A11
Technologies with low attractiveness	T52, T54, T55, T56	Growth & expansion	A3, A6, A7, A12, A13
Moderately attractive technologies	T1, T3, T19, T25, T26, T27, T28, T30, T31, T34, T36, T39, T40, T42, T43, T44	Market value	A1, A4, A9, A10
Average technologies	T2, T5, T6, T7, T9, T10, T11, T12, T13, T14, T15, T29, T32, T35, T37, T38, T41, T46, T47, T48, T49, T50, T51, T53, T57	Regional Integration	A5
Feasibility			
Technologies with very low feasibility	T52, T54, T55, T56	Skills & infrastructure	F4, F5, F6
Moderately feasible technologies	T2, T6, T9, T10, T15, T35, T39, T40, T41, T43, T46, T47, T48, T49, T50, T51, T53	Market interest	F7
Technologies with the highest feasibility	T16, T17, T18, T20, T21, T23, T24, T25, T31	Technical feasibility	F3, F8
Highly feasible technologies	T1, T3, T4, T5, T7, T8, T11, T12, T13, T14, T19, T22, T26, T27, T28, T29, T30, T32, T33, T34, T36, T37, T38, T42, T44, T45, T57	Funding access	F1, F2

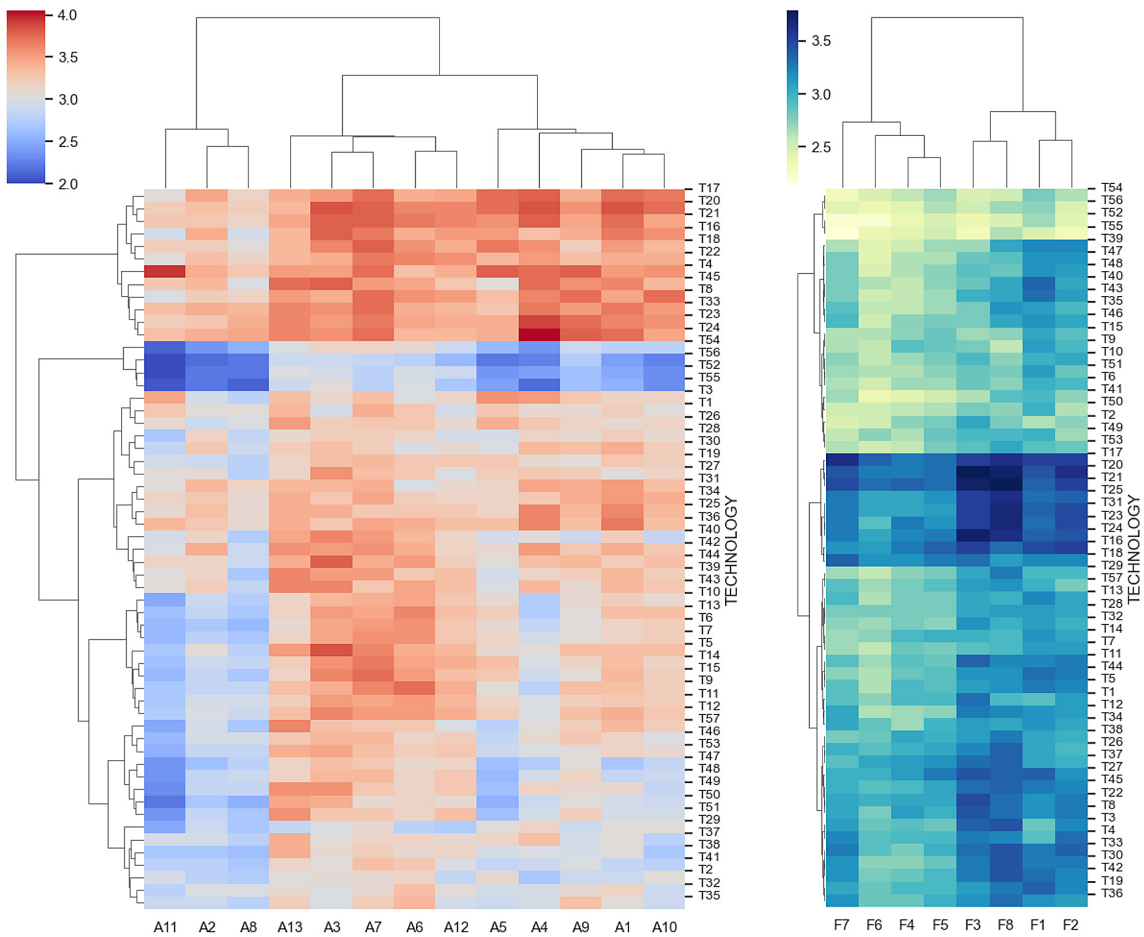

Figure 6. Cluster heatmaps – attractiveness and feasibility

Table 6. Co-clustered technologies and thematic attribute groups for attractiveness and feasibility dimensions

<table>
<tr><th>Cluster</th><th>Technology</th><th>Features</th></tr>
<tr><td colspan="3">Attractiveness</td></tr>
<tr><td>Regional synergy and industrial readiness</td><td>T1, T2, <u>T3</u>, <u>T4</u>, <u>T16</u>, <u>T17</u>, <u>T18</u>, T19, <u>T20</u>, <u>T21</u>, <u>T22</u>, <u>T26</u>, T27, T29, <u>T36</u></td><td>A5 – Use of regional potential
A10 – Entrepreneurship stimulation
A11 – Absorption in existing industry</td></tr>
<tr><td>Frontier technologies for emerging sectors</td><td>T46, T47, T48, T49, T50, T51, T52, T53, T56, T57</td><td>A3 – R&D activity
A13 – Absorption in emerging sectors</td></tr>
<tr><td>Next-gen precision medicine and therapies</td><td><u>T5</u>, T6, T7, T9, T10, <u>T11</u>, <u>T12</u>, T13, T14, T15, T54, T55</td><td>A6 – Competitiveness
A7 – Enterprise positioning
A12 – Broad dissemination</td></tr>
<tr><td>Sustainable development and societal impact</td><td><u>T8</u>, <u>T23</u>, <u>T24</u>, <u>T25</u>, T28, T30, <u>T31</u>, T32, <u>T33</u>, <u>T34</u>, T35, T37, T38, T39, T40, T41, <u>T42</u>, T43, <u>T44</u>, <u>T45</u></td><td>A1 – Investment attractiveness
A2 – Private R&D growth
A4 – Commercialisation ease
A8 – Job creation
A9 – Economic efficiency</td></tr>
<tr><td colspan="3">Feasibility</td></tr>
<tr><td>Strong infrastructure and skilled workforce</td><td>T1, T2, <u>T16</u>, <u>T18</u>, <u>T26</u>, T27, T37, T38, T49, T55</td><td>F4 – Human resource quality
F5 – Qualified personnel
F6 – R&D infrastructure</td></tr>
<tr><td>Business-driven and technically viable</td><td><u>T3</u>, <u>T4</u>, <u>T8</u>, <u>T11</u>, <u>T12</u>, <u>T17</u>, <u>T20</u>, <u>T21</u>, <u>T22</u>, <u>T23</u>, <u>T24</u>, <u>T25</u>, T28, T29, T30, <u>T31</u>, T32, <u>T33</u>, <u>T34</u>, <u>T36</u>, <u>T42</u>, <u>T45</u>, T53, T57</td><td>F3 - Technical feasibility
F7 – Business interest
F8 – Equipment availability</td></tr>
<tr><td>Financially ready and scalable</td><td><u>T5</u>, T13, T19, T35, T39, T40, T41, T43, <u>T44</u>, T46, T47, T48</td><td>F1 – Access to funding
F2 – Financial feasibility</td></tr>
<tr><td>Advanced research and experimental potential</td><td>T6, T7, T9, T10, T14, T15, T50, T51, T52, T54, T56</td><td>(No feasibility features assigned)</td></tr>
</table>

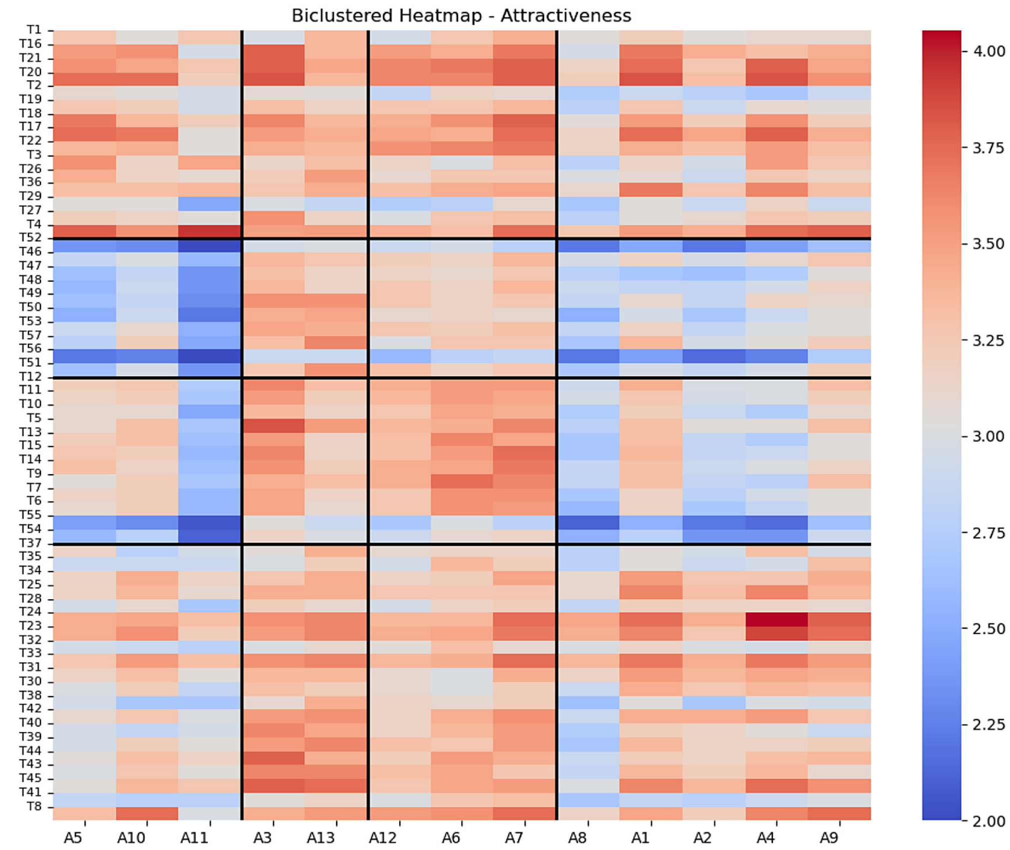

Figure 7. Co-clustered of technology attractiveness based on expert evaluation

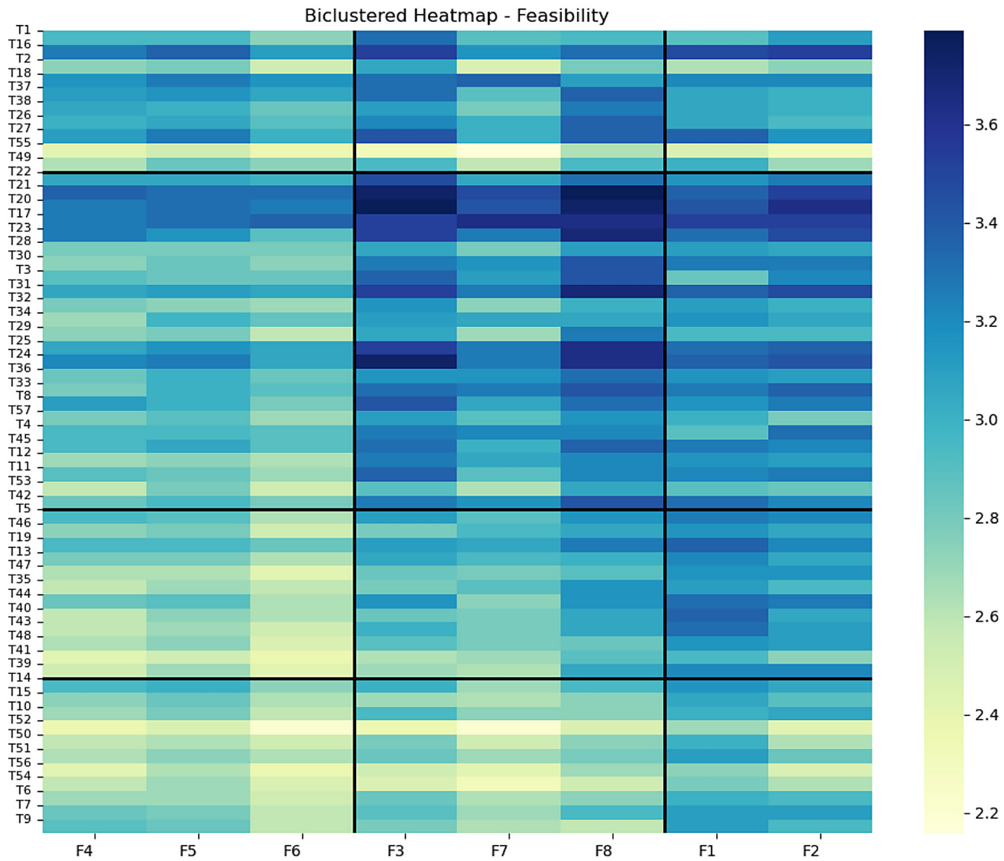

Figure 8. Co-clustered of technology feasibility based on expert evaluation

analysis and provide a solid basis for evidence-based strategic recommendations.

Considering the implemented methods, one-dimensional hierarchical clustering enables the prioritisation of technologies for immediate action for long-term development. This approach simplifies decision-making by focusing on aggregated readiness levels but provides limited insights into the drivers of these ratings. While the joint evaluation of these two dimensions narrows the number of technologies selected, it does not significantly enhance precision nor contribute substantial new insights. In contrast, two-dimensional clustering, where technologies and features are clustered separately, involves first grouping technologies based on their attractiveness and feasibility scores, followed by independent clustering of the features themselves. The result is the formation of distinct groups of technologies and separate thematic clusters of features. This method adds interpretive value by showing which features most strongly influence each technology cluster. Co-clustering is a simultaneous two-dimensional clustering of technologies and features within a single matrix, and offers a more integrated approach. It enables the identification of shared patterns between technologies and features, facilitating the assignment of technologies to strategic thematic groups that reflect both attractiveness and feasibility. As a result, coherent clusters of technologies and features emerge, supporting a more holistic understanding of the innovation landscape and providing a stronger foundation for strategic planning.

Expert clustering analysis

Expert analysis and clustering of expert judgments is the second area addressed in this work. The goal is to assess the consistency, behavioural patterns, congruence, and quality of expert judgments. The proposed GenAI approaches include correlation and network analysis, as well as expert behaviour analysis. Expert behaviour analysis facilitates the identification of inconsistent or extreme ratings, which may be excluded or examined as distinct cases. It evaluates whether experts with limited knowledge exhibit different rating patterns, such as lower ratings and a lack of differentiation.

The project gathered the opinions of 19 experts (E_1, E_2, …, E_19). Clustering of in two-dimensional space: mean attractiveness rating versus mean feasibility rating grouped experts into three clusters based on the evaluation schemes: Cluster 0 – experts with higher, consistent ratings of both attractiveness and feasibility; Cluster 1 – experts with more critical or highly variable ratings; Cluster 2 – moderate ratings (Figure 9).

When analysing the aggregated results of the relationship between the average level of expert knowledge and the average assessment of technology feasibility, both Pearson and Spearman correlation coefficients indicated negative and moderate correlations. This suggests that higher expert knowledge is associated with lower evaluations of both attractiveness and feasibility of technologies. Detailed correlations between knowledge and individual criteria are illustrated in Figure 10 and 11.

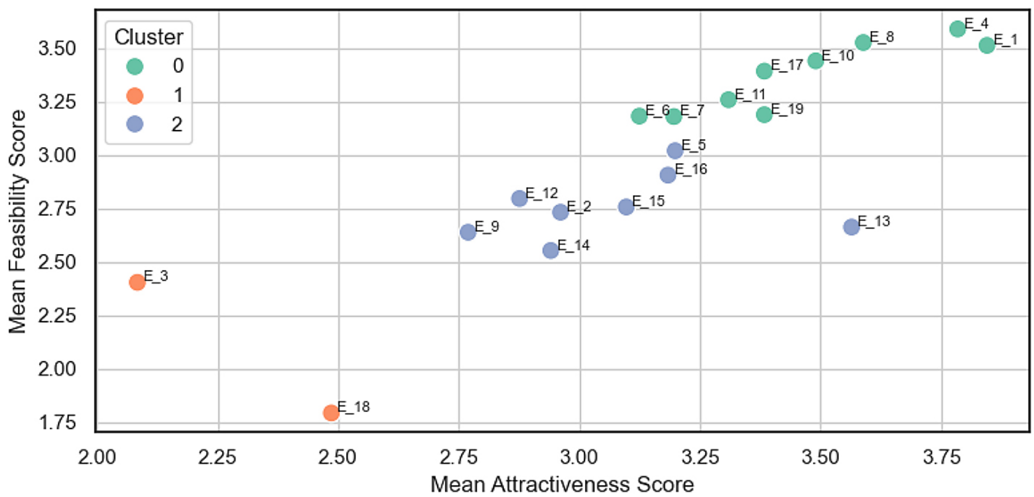

Figure 9. Clustering of in two-dimensional space: mean attractiveness rating versus mean feasibility rating

In the feasibility domain, expert knowledge often correlates negatively with assessments – more knowledgeable experts tend to give lower feasibility scores, likely due to greater awareness of risks and barriers. For attractiveness, the relationship varies by domain and criterion, but negative correlations also appear often, especially in complex or highly regulated sectors. Examples: in medicine and environmental protection, experts with high knowledge are more critical, likely due to their understanding of implementation challenges. In contrast, in machinery and transport, experts are more optimistic – knowledge tends to support higher evaluations. In the clothing and wood industries, knowledge has little or no negative impact, possibly due to lower technological or institutional barriers.

GenAI also suggests analysing expert similarity networks (Figure 12).

The analysis of expert similarity networks enables an understanding of how consistent the individual evaluation patterns are, both in terms of the attractiveness and feasibility of the assessed technologies. Identifying groups of experts who provide similar assessments can indicate shared experience, knowledge, or decision-making perspectives. This allows for the identification of natural "schools of thought" within the evaluation team. Network density and the number of connections may suggest cohesion or fragmentation of opinions within the expert group, as well as highlight the experts with unique evaluation profiles who may represent alternative approaches or potential sources of innovative insights.

The analysis revealed a tightly connected core cluster of experts, indicating a strong consensus in evaluating the attractiveness and feasibility of technologies. Peripheral experts (e.g., E_7,

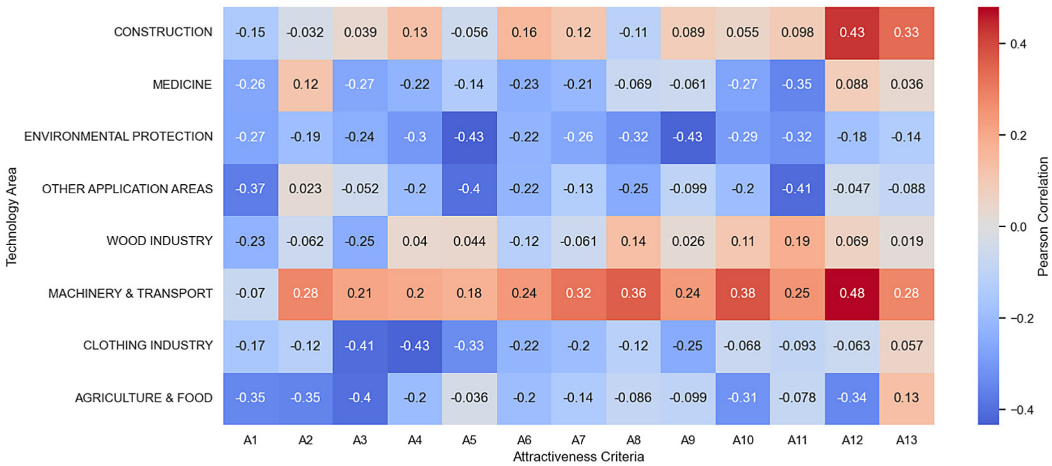

Figure 10. Correlation between knowledge level and attractiveness criteria by area

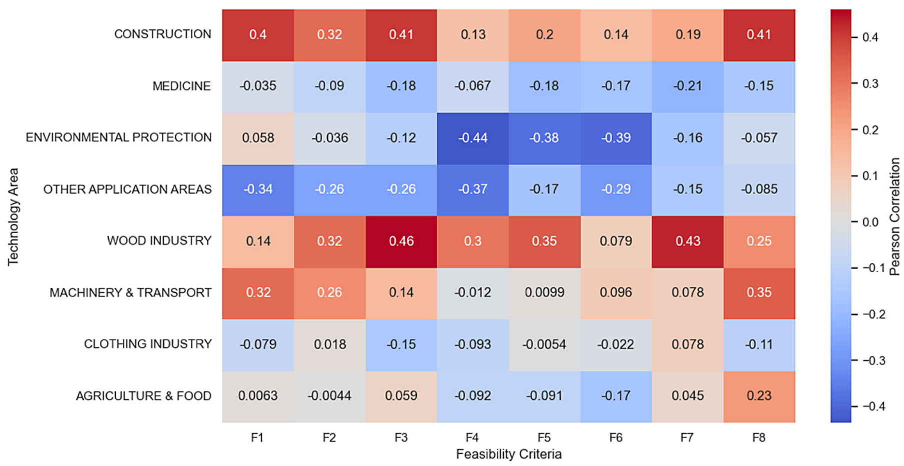

Figure 11. Correlation between knowledge level and feasibility criteria by area

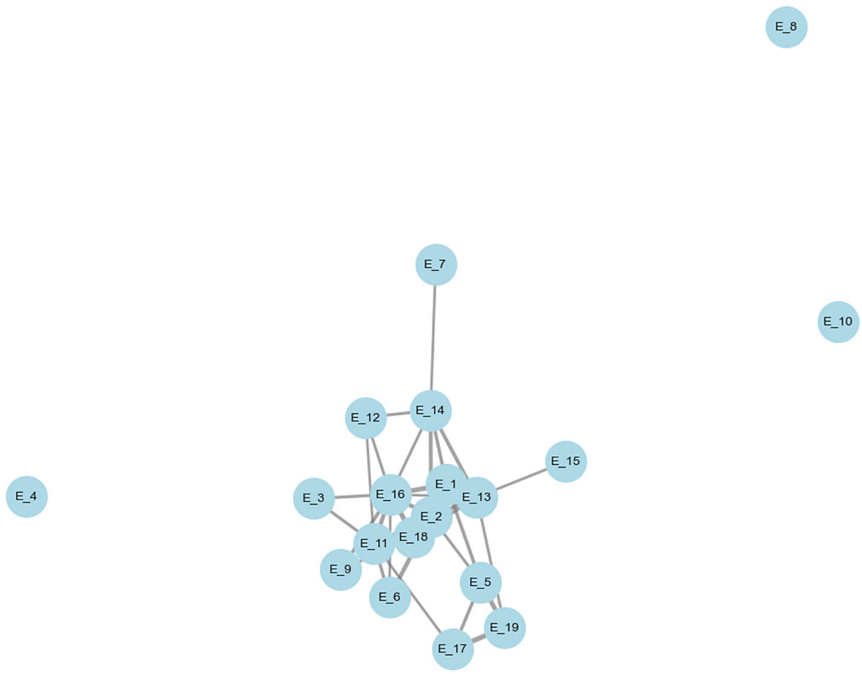

Figure 12. Expert similarity network on concatenated attractiveness and feasibility

E_15) showed partial alignment, while E_4, E_8, and E_10 represented clear outliers with distinct evaluation profiles. Such divergence, although reducing overall cohesion, can provide valuable alternative perspectives and highlight overlooked risks or opportunities. Expert similarity networks, therefore, not only capture the degree of consensus but also support balanced expert selection by integrating mainstream and minority viewpoints.

OPPORTUNITIES AND CONSIDERATIONS OF ARTIFICIAL INTELLIGENCE IN FORESIGHT

Artificial intelligence is currently a widely discussed topic, attracting growing interest across various fields. In many applications, it has already proven effective in supporting detection and diagnostic tasks [46]. While much of the literature emphasises the productivity gains associated with AI, counterarguments are also emerging– for example, that the current AI tools may actually slow down experienced professionals in certain tasks [47]. Nevertheless, benchmark studies show that the performance of leading AI models continues to improve steadily [48]. As for 2025, AI equals or outperforms in optimisation, but it does not equal creativity. In foresight-related applications, generative AI offers agent-based systems that integrate data access (e.g., web browsing), information synthesis, and natural dialogue. The quality of the output is often comparable to that produced by human experts. As such, AI support can provide new perspectives for the data-driven technology foresight. However, these tools still require human oversight to ensure the relevance and accuracy of their outputs.

In the literature, hybrid approaches combining AI and human experts are typically considered in patent data analysis, bibliometrics, or automated analysis of text data using NLP. Such integration allows for combining computational efficiency with expert interpretation, strengthening both the reliability and interpretability of results. Moreover, researchers can use LLMs not only as analytical tools, but also to design questions that foster critical thinking and logical reasoning skills.

The role of AI in increasing the accuracy, efficiency, and explainability of predictive technology assessment cannot be overstated. AI undoubtedly brings more benefits than risks (e.g., hallucinations, repetition of errors), especially when applied transparently and in combination with expert-driven processes. The LLM-based tools offer interesting opportunities for streamlining data analysis, enabling rapid identification of patterns, and supporting multidimensional assessments. Importantly, in an era when

LLMs are often used to generate abbreviated or even misleading outputs, this study highlights a constructive and methodologically transparent use case for these technologies in complex foresight processes.

The article focused on the clustering of technologies and the identification of expert groups, demonstrating that the data obtained through the foresight process can be interpreted from multiple perspectives. Rather than aiming for a single, definitive classification of technologies, this approach emphasises the further conditional and contextual characteristics of similarities. This allows for the identification of both coherent groups with similar assessment profiles and distinct, separate clusters. Although it does not provide significant implications for the final selection of the most important technologies – and in this case, it is worth using simple and understandable methods – it may provide new knowledge for additional interpretations of data.

The article also addressed the issue of expert analysis. Experts are a key element of the prioritisation process, and their knowledge and experience form the basis for preparing a list of key technologies, evaluation attributes, and often also the value of the criteria (as in the NT FOR project). Appropriate expert selection ensures a broad perspective and consideration of the views of multiple stakeholders. At the same time, in each case, the use of expert constraints is equivalent to adopting a subjective and uncertain framework for analysis. The approaches proposed by GenAI are ex post approaches– checking the consistency of assessments and dependencies, identifying experts who are significantly outliers. Given that the analyses have already been performed, these suggested approaches can only confirm the accuracy of the defined set of experts.

Considering further directions of research, it is also important to note that the original project under review did not fully address the issue of attribute weighting, which is crucial in technology assessment. Including such considerations could improve analytical depth by capturing differences in perceived importance between attractiveness, feasibility, or other evaluation criteria. This would have allowed for placing the analysis within the wide family MCDA methods, such as AHP, TOPSIS, or PROMETHEE. Therefore, it was not introduced in this analysis. Moreover, robustness remains a key challenge in many types of analysis [49], and foresight is no exception. The variability of results depending on the chosen method, attributes, and experts should be viewed not only as a limitation but also as a valuable opportunity for discussion and critical reflection. A posteriori analysis could help answer questions such as: How many criteria are needed to create a reliable ranking? What is the appropriate number of experts? Is an average rating useful, or should more emphasis be placed on divergent or extreme opinions? An interesting extension of the expert-based technology assessment would be to employ GenAI models to replicate the evaluation process and compare the results with human expert judgments. However, in this case, the key limitation lies in the passage of time, as the AI-based assessment would rely on a different set of information and contextual factors than those available to the original experts.

Table 7 summarises the main opportunities and considerations of AI in foresight projects.

We are undoubtedly entering a new era of foresight – one that requires changes not only in tools and methods but also in our way of thinking. Automated analyses will allow for the easy presentation of diverse perspectives, the exploration of interdependencies, the identification of possible interpretations, and the creation of a broad scope for further scenario-based analyses. This article used LLMs to generate inspiration, analysis, and computation, while maintaining oversight and assuming full responsibility for the text. As such, it can serve as a guide for using AI.

Table 7. Opportunities and considerations of AI in foresight

Opportunities	Considerations / Limitations
Increased efficiency in data processing and clustering	AI-generated outputs require human oversight to ensure contextual accuracy
Rapid identification of thematic groups and patterns	Risk of hallucinations and propagation of errors
Supports multi-perspective interpretation and scenario building	Robustness issues due to sensitivity to method, experts, and attributes selection
Enhanced explainability and identification of outliers in data	Current AI tools remain limited in creativity and contextual nuance

CONCLUSIONS

This study examined how AI can enhance technology foresight by integrating a systematic literature review with an experimental analysis of empirical data from the NT FOR Podlaskie 2020 project.

The literature review revealed that AI is increasingly integrated into foresight, primarily in conjunction with scenario planning, trend analysis, Delphi methods, bibliometrics, and clustering. Machine learning, natural language processing, and large language models emerge as key tools for processing large datasets and enhancing expert-based evaluations, while the potential for automating numerical analysis remains underestimated. The review also showed a conceptual inconsistency in terminology: "artificial intelligence" dominates, whereas terms such as "machine learning" and "deep learning" are underused, despite frequent references to "neural networks."

In the empirical part, generative AI was applied to recommend analytical techniques and generate Python code for efficient data processing. Hierarchical clustering, biclustering, and expert similarity networks were applied to the NT FOR dataset. These methods revealed coherent technology groups, thematic attribute clusters, and distinct expert groups.

The key results can be summarised as follows:

- AI-generated suggestions remained within conventional frameworks and required expert oversight for contextual validation.
- AI-assisted foresight provided deeper insights than traditional averaging, enhancing interpretability and robustness.
- Expert network analysis identified a consensus group and outliers, showing both cohesion and diversity of views.

Overall, the integration of AI into foresight enriches the analytical process by enabling dynamic, multi-perspective analyses that combine computational efficiency with expert judgment. Such hybrid approaches both strengthen the explanatory value of foresight and provide practical guidance for strategic technology assessment, while maintaining the crucial role of expert knowledge in shaping valid and actionable outcomes.

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