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**Enhancing strategic roadmapping through the integration of topic modeling and
generative AI**

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André Magalhães Gomes

**Enhancing strategic roadmapping through the integration of topic modeling and
generative AI**

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ATA

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ATA DA DEFESA DE TESE EM ADMINISTRAÇÃO do Senhor **ANDRÉ MAGALHÃES GOMES** REGISTRO Nº 334/2025. No dia 28 de maio de 2025, às 07:00 horas, reuniu-se de forma remota, por videoconferência, a Comissão Examinadora de Tese, indicada pelo Colegiado do Centro de Pós-Graduação e Pesquisas em Administração do CEPEAD, em 28 de abril de 2025, para julgar o trabalho final intitulado "ENHANCING STRATEGIC ROADMAPPING THROUGH THE INTEGRATION OF TOPIC MODELING AND GENERATIVE AI", requisito para a obtenção do Grau de Doutor em Administração, linha de pesquisa: Estratégia, Mercadologia e Operações. Abrindo a sessão, o Senhor Presidente da Comissão, Prof. Dr. Jonathan Simões Freitas, após dar conhecimento aos presentes o teor das Normas Regulamentares do Trabalho Final, passou a palavra ao candidato para apresentação de seu trabalho. Seguiu-se a arguição pelos examinadores com a respectiva defesa do candidato. Logo após, a Comissão se reuniu sem a presença do candidato e do público, para julgamento e expedição do seguinte resultado final:

☒ APROVAÇÃO

☐ REPROVAÇÃO

O resultado final foi comunicado publicamente ao candidato pelo Senhor Presidente da Comissão. Nada mais havendo a tratar, o Senhor Presidente encerrou a reunião e lavrou a presente ATA, que será assinada por todos os membros participantes da Comissão Examinadora. Belo Horizonte, 28 de maio de 2025.

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RESUMO

As práticas contemporâneas de roadmapping estratégico são cada vez mais influenciadas pela digitalização e inteligência artificial (IA), porém a integração de técnicas avançadas de IA nos processos de roadmapping permanece limitada. Esta tese investiga como abordagens aumentadas por IA, particularmente modelagem neural de tópicos e IA generativa, podem aprimorar o roadmapping estratégico. A pesquisa inicia com uma revisão sistemática abrangente da literatura desde o início dos anos 1980, utilizando bibliometria e modelagem de tópicos para catalogar a evolução das aplicações de IA em roadmapping, revelando avanços metodológicos significativos, mas também lacunas significativas na implementação prática. Abordando essa lacuna entre pesquisa e prática, desenvolvemos e avaliamos um artefato inovador que combina modelagem neural de tópicos com IA generativa através de Geração Aumentada por Recuperação (RAG) para extrair insights estrategicamente relevantes para a fase de pré-população do roadmapping, garantindo confiabilidade através de fundamentação explícita em documentos-fonte. O artefato evoluiu através de duas aplicações distintas: primeiro, uma prova de conceito inicial no domínio AgeTech que utilizou BERTopic para agrupamento e rotulação de tópicos, demonstrando viabilidade com 44% dos tópicos finais do roadmap derivados de análise quantitativa; segundo, uma implementação aprimorada incorporando capacidades RAG para produzir relatórios baseados em tópicos com referências científicas de apoio. Este artefato refinado foi aplicado em AgeTech e validado em oito estudos de caso ao vivo, demonstrando como tópicos gerados por IA podem efetivamente aumentar as camadas de mercado, produto e tecnologia de roadmaps estratégicos em ambientes do mundo real. Avaliações de especialistas confirmaram alta confiabilidade (98,7% dos tópicos considerados confiáveis) e relevância estratégica em diferentes contextos de roadmapping. Os resultados demonstram como o roadmapping aumentado por IA pode aprimorar a previsão estratégica enquanto mantém os pontos fortes visuais e colaborativos que tornam o roadmapping tradicional eficaz, permitindo que as organizações desenvolvam roadmaps estratégicos mais abrangentes e baseados em evidências.

Palavras-chave: Roadmapping Estratégico; Processamento de Linguagem Natural; Modelos de Linguagem de Grande Escala; Modelagem Neural de Tópicos; Geração Aumentada por Recuperação; IA Generativa.

ABSTRACT

Contemporary strategic roadmapping practices are increasingly influenced by digitalization and artificial intelligence (AI), yet integrating advanced AI techniques into roadmapping processes remains limited. This thesis investigates how AI-augmented approaches, particularly neural topic modeling and generative AI, can enhance strategic roadmapping. The research begins with a comprehensive systematic review of literature dating back to the early 1980s, using bibliometrics and topic modeling to catalog the evolution of AI applications in roadmapping, revealing significant methodological advancements but also significant gaps in practical implementation. Addressing this research-practice gap, we developed and evaluated an innovative artifact that combines neural topic modeling with generative AI through Retrieval Augmented Generation (RAG) to extract strategically relevant insights for the pre-population phase of roadmapping while ensuring reliability through explicit grounding in source documents. The artifact evolved through two distinct applications: first, an initial proof-of-concept in the AgeTech domain that utilized BERTopic for clustering and topic labeling, demonstrating feasibility with 44% of final roadmap topics derived from quantitative analysis; second, an enhanced implementation incorporating RAG capabilities to produce topic-based reports with supporting scientific references. This refined artifact was applied in AgeTech and validated across eight live case studies, demonstrating how AI-generated topics can effectively augment the market, product, and technology layers of strategic roadmaps in real-world settings. Expert evaluations confirmed high reliability (98.7% of topics deemed reliable) and strategic relevance across different roadmapping contexts. The results demonstrate how AI-augmented roadmapping can enhance strategic foresight while maintaining the visual and collaborative strengths that make traditional roadmapping effective, enabling organizations to develop more comprehensive, evidence-based strategic roadmaps.

Keywords: Strategic Roadmapping; Natural Language Processing; Large Language Models; Neural Topic Modeling; Retrieval Augmented Generation; Generative AI.

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1. INTRODUCTION

1.1. ROADMAPPING: FROM EXPERTS APPROACHES TO AI INTEGRATION

Roadmapping, as a strategic planning tool, utilizes a visual representation of data to enhance an organization's understanding of its course of action, self-perception, and business conception (Kerr and Phaal 2022). Widely used since its introduction in a 1945 Harvard Business Review paper (Massel 1945), with subsequent adoption by corporations like Motorola and Boeing (Kerr 2020; Willyard 1987), roadmapping has gained significant traction.

The relevance of the expert-based approach, promoted by the University of Cambridge, merging technology, innovation, and strategic management tools (Ker et al. 2011), is generally emphasized in practical applications. Beyond that, the computer-based approach deployed by the Seoul school aids in generating roadmaps using software tools (Park 2020). Meanwhile, bibliometrics-based roadmapping, an offshoot of the computer-based approach, which integrates empirical indicators drawn from extensive databases of articles, has also been acknowledged for its innovative contribution to roadmapping methodology (Park 2020). However, the potential of data mining and neural networks in building strategic plans is yet to be fully utilized (Eroglu and Kilic 2017).

When considering roadmapping in the digital age, it is essential to understand how technological advancements, including big data, self-learning algorithms, and robust computation, have spurred the development of AI-based systems for problem-solving tasks requiring human intelligence (Keding 2020; Mitchell 2019). This evolution has fueled discussion surrounding the augmentation of human managers with intelligent machines and their impact on organizational assumptions (Huang 2019). As creativity is central to innovation success, there is growing interest in how artificial intelligence can augment human capabilities, especially in strategic innovation processes like roadmapping (Rupprecht and Mayrhofer 2024). Intelligent systems have been increasingly used to create comprehensive search and innovation discovery (Bahceci, Katila, and Miikkulainen 2023) strategies and variable creation based on unstructured text data (Helfat et al. 2023). However, gaps persist in comprehending AI's strategic role, particularly in understanding how to effectively integrate AI's capabilities with human expertise in strategic roadmapping contexts (Keding 2020).

Specifically, the research on digitalization roadmapping is multifaceted and comprehensive, revolving around four pivotal areas: strategy formulation, landscaping, social interaction, and digital information management (Oliveira et al. 2023). Substantial attention is drawn towards discerning the link between roadmapping digitalization and performance, which necessitates understanding roadmapping context data use, including organizational context, team experience, and implementation maturity (Hirose et al. 2020).

The landscape of AI technologies applicable to strategic roadmapping encompasses several distinct but interconnected categories. Natural language processing (NLP) techniques convert qualitative information in unstructured textual data into novel and valuable quantitative insights (Choi, Menon, and Tabakovic 2021), enabling the transformation of text documents into AI-driven insights for strategic development (Gentzkow, Kelly, and Taddy 2019). Meanwhile, knowledge representation systems can formalize domain expertise to enhance roadmapping processes. When properly integrated, these AI capabilities can augment human cognitive abilities in navigating and interpreting nuances within millions of documents (Evans and Aceves 2016), providing a technical foundation for the strategic augmentation of roadmapping processes.

The recent advancements in technology and artificial intelligence (AI) can be considered to increase performance on strategic roadmapping. Primarily, the availability of big data, self-learning algorithms, and the increasing power of computers have facilitated the development of AI-based systems (Keding 2020). These AI applications are designed to solve problems that require human intelligence (Mitchell 2019). These developments have initiated a discussion about the future of traditional organizational assumptions and the potential augmentation of human managers using intelligent machines (Huang 2019).

Intelligent systems are on the rise in unstructured environments (Di Ciccio 2014), aiding decision-making, which is essential for strategic outcomes and gaining competitive advantage (Davenport 2016; Kiron and Schrage 2019; von Krogh 2018). Also, it is increasingly popular for solving different business problems (Lee 2018; Phan 2017). Despite the growing literature on AI's business potential and the research field's supposed maturity, there is still a gap in understanding how AI fits into strategic roadmapping (Keding 2020).

Most research on Data analytics has focused only on the technical aspects, often overlooking the business and management perspectives, which have only recently started to

explore the benefits of big data analytics for strategic purposes (Ardito 2019). In a review of artificial intelligence (AI) applications in strategic management from 1989 to 2019, the majority of the most significant and high-quality advancements occurred between 2016 and 2019 (Keding 2020). This highlights the rapid and substantial progress in the field within the last few years.

Following that, given the advantages, the availability of data, and the improved user-friendliness of software packages, research on artificial neural networks in business remains a fertile ground for discovery. A review of artificial neural networks in business by Tkác and Verner (2016) predicts that neural networks will draw more authors and usher in novel application opportunities. Current literature points towards the capacity of artificial intelligence (AI) in decision-making as a tool to mitigate data overload (Keding 2020).

While some researchers consider the role of AI in strategy to be overstated, most anticipate its most beneficial impact in augmenting managers' capacities (Agrawal, Gans, and Goldfarb 2017). Scholars argue that traditional strategy approaches are becoming less effective in business environments transformed by emerging technologies. However, AI can potentially expand the range of organizational knowledge incorporated into strategy development (Keding 2020).

1.2. TOPIC MODELING: ADVANCING STRATEGIC ANALYSIS

Among these AI-driven techniques, topic modeling has emerged as a crucial method for incorporating AI advancements into strategic planning research, particularly in investigating complex social issues and bridging social science with data analytics (Hannigan et al. 2019). When applied to roadmapping, topic modeling serves multiple critical functions: identifying emerging technological trends from vast document collections, mapping competitive landscapes through analysis of patents and publications, and discovering latent connections between seemingly disparate technology fields. These models provide a robust, quantitative method to discern concealed themes within collections of documents, exposing latent patterns and connections that remain hidden in unprocessed data (Prollochs and Feuerriegel 2020). Specifically, within the roadmapping process, topic modeling can enhance the pre-population phase by systematically analyzing external environment signals, identifying patterns in vast quantities of documents. This research focused specifically on this pre-population step as a critical phase where AI augmentation

could provide the most significant value to the roadmapping process, as it addresses the challenge of systematically preparing relevant strategic topics before collaborative workshops begin.

Topic modeling techniques have risen to prominence as critical instruments in the investigation of complex social issues, functioning as a link bridging social science with both structured and unstructured data analysis, diverse forms of deductive reasoning, and the rapidly expanding discipline of large-scale data analytics (Hannigan et al. 2019). These models provide a robust, quantitative method to discern concealed themes within a collection of documents, exposing latent patterns and connections that remain hidden in unprocessed data (Prollochs and Feuerriegel 2020).

Topic models, such as LDA (Blei, Ng, and Jordan 2003) and Non-Negative Matrix Factorization (NMF) (Févotte and Idier 2011), have demonstrated their power as unsupervised tools. By considering each document as a “bag of words” and representing it as a blend of hidden topics, these models provide an advanced method to reveal prevailing themes and inherent narratives in textual data. Employing such models can unearth more profound insights into the intricacies of social phenomena and how we scrutinize and comprehend them.

Nonetheless, despite their advantages, these techniques come with certain drawbacks. One notable weakness of the prevalent Bag-of-Words (BoW) models lies in the significant semantic information loss during the development of the codebook, a crucial step in the BoW approach (Lei Wu, Hoi, and Nenghai Yu 2010). Consequently, these models might fail to fully capture the true nature of documents by overlooking the contextual relationships of words within texts.

To overcome this limitation, the field of natural language processing has seen a significant rise in the use of text embedding methods. In particular, Bi-directional Encoder Representations from Transformers (BERT) (Devlin et al. 2018) has shown outstanding ability in not only recognizing synonyms but also in understanding words with varying meanings depending on their context.

Recent advancements in neural topic models have demonstrated considerable progress by integrating the capabilities of neural networks with traditional topic modeling approaches (Cao 2015). This progress is particularly evident in effectively incorporating word embeddings into established models, like LDA, highlighting the benefits of advanced representational techniques in refining the precision of topic models (Jiang, 2017; Phan et al., 2015). Amongst these

techniques, BERTopic has shown superior performance in incorporating the latest developments of neural networks in traditional topic modeling approaches (Grootendorst 2022).

As depicted in Figure 1, BERTopic merges clustering methodologies with an innovative version of Term Frequency-Inverse Document Frequency (TF-IDF) tailored for classes, enabling the generation of distinct and coherent topics. The process underpinning BERTopic is structured into three main phases: initially, it generates document embeddings using pre-trained language models; then, it applies dimensionality reduction to these embeddings, clustering documents by their semantic similarities; finally, it utilizes a class-specific variant of TF-IDF to extract topics from each group. The adaptable design of BERTopic facilitates its utilization across a broad spectrum of scenarios (Grootendorst 2022).

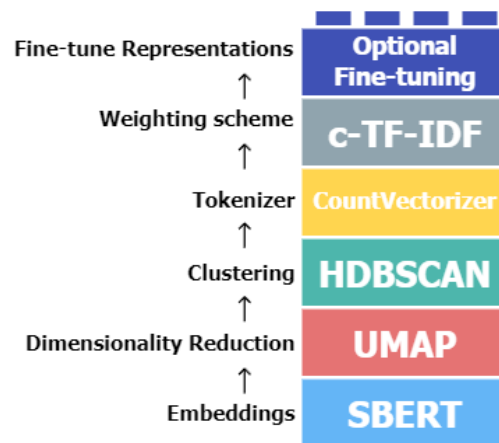


Fig. 1 Creating topic representations in BERTopic (Grootendorst 2022).

To capture the essence of semantic similarity in a multidimensional space, BERTopic employs the Sentence-BERT (SBERT) architecture (Reimers and Gurevych 2019), creating vector representations of documents. Using advanced pre-trained language models, the SBERT method transforms sentences and paragraphs into concise vector formats. Consequently, these vector representations carry significant semantic value, enhancing their utility in tasks like semantic search and data clustering (Cheng et al. 2023).

However, dealing with data in high dimensions presents challenges, primarily due to the curse of dimensionality (Aggarwal, Hinneburg, and Keim 2002). To mitigate this issue dimensionality reduction is performed using Uniform Manifold Approximation and Projection

(UMAP), which effectively preserves the local and global characteristics of the data in fewer dimensions (McInnes 2018).

The HDBSCAN algorithm clusters these dimensionally reduced data points (McInnes et al. 2017). This method builds upon DBSCAN to accommodate clusters of varied densities and effectively segregate outliers. Utilizing the hierarchical structure produced by HDBSCAN allows for effectively identifying and extracting clusters (Stewart and Al-Khassaweneh 2022).

In defining topics, BERTopic considers each cluster to represent a single topic derived from the aggregate of documents. This approach alters the traditional TF-IDF measure, which quantifies a word's relevance to a document, to assess a term's relevance to a topic instead. Treating each cluster as a collective document recalibrates the TF-IDF scores, employing inverse class frequency instead of inverse document frequency to evaluate a term's contribution to a class (e.g. Kwon, Yoo, and Lee 2024). This technique shifts the focus to the significance of terms across clusters, enabling the generation of distinct topic-word distributions for each cluster. Finally, in the optional finetuning, many different language models can be used, with GPT-4o (OpenAI et al. 2024) providing the best performance in the LMSYS leaderboard, an open-source platform for evaluating LLMs based on human preferences (Chiang et al. 2024).

These technical advancements in topic modeling coincide with broader questions about AI's role in strategic management. Evidence suggests that AI's significant value lies in augmenting managerial capabilities (Agrawal et al. 2017). This augmentation becomes important as traditional strategic approaches struggle to adapt to rapidly evolving business landscapes, especially in emerging technology sectors where the volume and complexity of information exceed human cognitive capacity.

Building on this need for augmentation, retrieval-augmented generation (RAG) has emerged as a promising direction for enhancing strategic decision-making processes while addressing key limitations of earlier AI approaches. By grounding generative AI outputs in verified information sources, RAG techniques address critical challenges like hallucination and false information generation that have limited AI's reliability in strategic contexts (Bommasani et al. 2022; Kenton et al. 2021). The integration of neural topic modeling with RAG capabilities offers a potential pathway to combine the pattern-recognition strengths of topic modeling with the factual reliability needed for strategic planning, setting the stage for new approaches to AI-

augmented roadmapping that can better serve organizations navigating complex technological landscapes.

1.3. PROBLEM AND RESEARCH QUESTION

Strategic roadmapping methodologies face challenges in the digital era as organizations navigate increasingly complex technological landscapes. Traditional data-driven roadmapping approaches—including keyword-based visual analysis (Kim et al., 2016), bibliometrics (Bildosola 2017), or traditional text mining (Khademi, Lampela, and Smyrniotis 2021)—exhibit substantial limitations in their ability to process and derive meaningful insights from large volumes of unstructured data.

Despite the growing literature on artificial intelligence applications in business contexts, a significant research gap exists in understanding how to effectively integrate AI capabilities into strategic processes (Keding 2020). While AI has demonstrated potential in augmenting managerial decision-making (Agrawal et al. 2017), its application to roadmapping remains underdeveloped. The challenge lies in how to systematically incorporate advanced AI technologies to enhance roadmapping while addressing issues of reliability that have limited previous AI applications (Bommasani et al. 2022; Kenton et al. 2021). The rapid evolution of neural topic modeling techniques (Grootendorst 2022) and retrieval-augmented generation (Lewis et al. 2021) presents new opportunities for strategic planning that have not been fully explored within roadmapping contexts.

Based on these research gaps, our central research question is: How can artificial intelligence, specifically the integration of neural topic modeling and retrieval-augmented generation, be systematically incorporated into strategic roadmapping processes to enhance the reliability of generated insights and augment human cognitive capabilities in strategic knowledge extraction and interpretation?

1.4. OBJECTIVES

The primary objective of this research is to investigate how artificial intelligence can be systematically integrated into strategic roadmapping processes, with a specific focus on

developing a design science artifact that combines advanced topic modeling and retrieval-augmented generation to enhance roadmapping. This research aims to:

1. Establish the theoretical foundation by analyzing the intersection of strategic roadmapping, digitalization, and artificial intelligence, identifying specific roadmapping stages and processes that present opportunities for AI augmentation.
2. Conduct a systematic review of existing research on AI applications in roadmapping, with particular attention to methodological approaches, limitations, and evaluation frameworks used in previous studies.
3. Design and develop an integrated AI-based artifact that combines neural topic modeling with retrieval-augmented generation techniques, specifically engineered to extract reliable strategic insights from unstructured data sources for roadmapping applications.
4. Implement and evaluate the developed artifact in real-world strategic roadmapping contexts across multiple industries.
5. Assess the performance of AI-augmented strategic roadmapping, focusing on three dimensions: the reliability of generated insights (factual accuracy and evidentiary basis), the relevance of identified topics to strategic decision-making contexts, and the usability of the generated topics for roadmapping practitioners.

1.5. A DESIGN SCIENCE RESEARCH

This research adopts a design science research (DSR) methodology to systematically develop and evaluate an artifact that addresses the practical challenges of strategic roadmapping in data-rich environments. Rooted in the science of the artificial (Simon 1968) and guided by established methodological frameworks (Akoka et al. 2023; Weigand, Johannesson, and Andersson 2021), DSR provides a rigorous approach for creating purposeful artifacts that solve real-world problems while contributing to theoretical knowledge.

According to Baker (2004), artifacts in design science research are created to fulfill a specific practical function. Here, the function is to augment strategic roadmapping with topic modeling and retrieval-augmented generative AI. Thus, the artifact developed in this research is a data-driven topic modeling system using neural networks and retrieval-augmented generation (RAG) protocols, specifically designed to augment strategic roadmapping processes. This

approach follows the core DSR principle of creating utility through designed artifacts while maintaining scientific rigor (Akoka et al. 2023; Simon 1968; Wieringa 2014). By combining the intellectual capacity of strategic decision-makers with advanced analytics capabilities, the artifact aims to enhance the effectiveness of strategic roadmapping activities, with a particular focus on the pre-population phase where relevant topics and insights are identified and prepared before the collaborative roadmapping workshops begin.

The DSR process employed in this research follows an iterative cycle of problem identification, artifact design, development, demonstration, evaluation, and communication. Initially, a comprehensive problem analysis was conducted through a systematic literature review to identify the specific challenges in current AI-driven roadmapping practices. This informed the design requirements for the artifact, emphasizing the development of a reliable augmented roadmapping approach.

In the development phase, the research integrates neural topic modeling (Grootendorst 2022) with custom-designed RAG components to create a system that extracts strategic insights from unstructured data while maintaining reliability. This approach uses neural topic models' strengths in capturing semantic relationships through word embeddings (Jiang 2017; Phan et al. 2015) while addressing their limitations through retrieval-augmented generation techniques.

The evaluation strategy employs a multi-method approach combining technical performance metrics with qualitative assessments from roadmapping practitioners across eight case studies. This mixed-methods evaluation examines the technical efficacy of the topic modeling, and the practical utility of the insights generated for strategic decision-making, aligning with DSR's dual focus on relevance and rigor.

Throughout the research, design knowledge is accumulated and formalized as design principles and theoretical contributions, providing actionable guidelines for integrating AI into strategic roadmapping. This approach to artifact development, evaluation, and knowledge contribution positions the research firmly within the design science tradition while addressing a significant practical challenge in roadmapping.

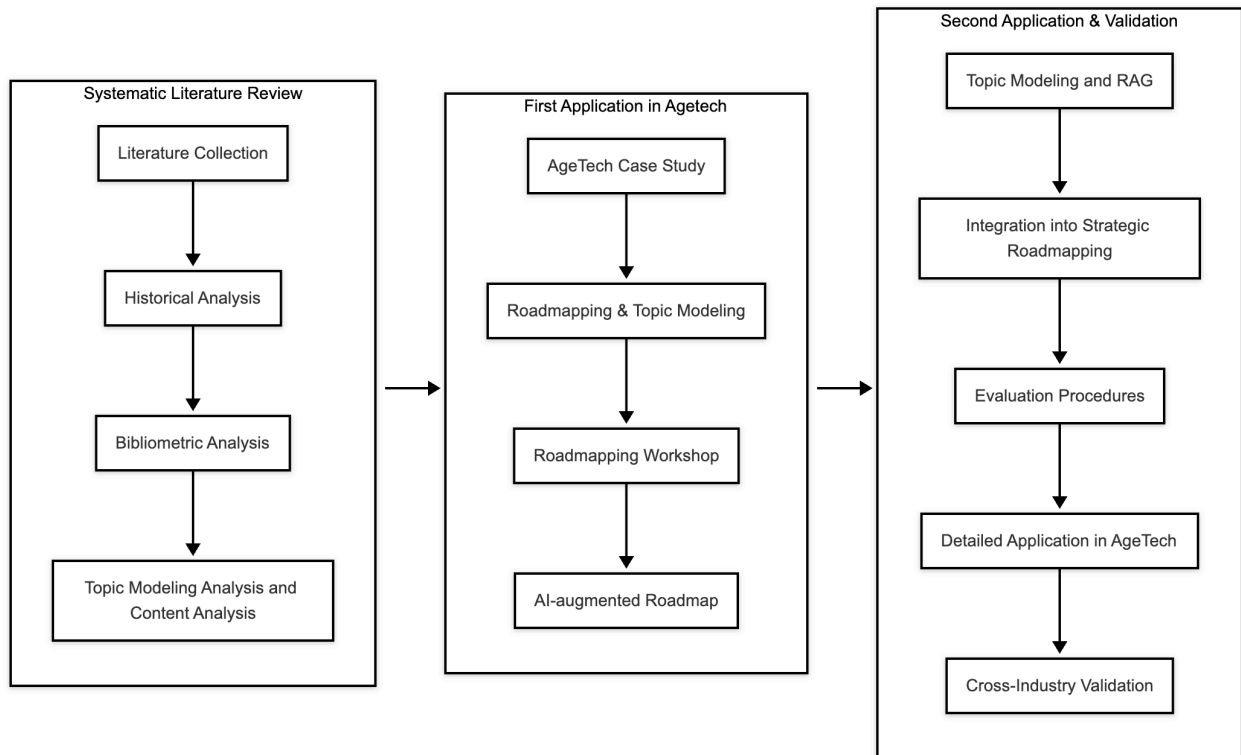


Fig. 2 Flowchart of the thesis

Therefore, this research follows a three-phase methodological framework as depicted in Figure 2, each phase represents a self-contained part of the thesis. In the first phase, a systematic literature review is conducted, proceeding sequentially through literature collection, historical analysis, bibliometric analysis, and finally topic modeling and content analysis. The second phase involves the initial application in AgeTech, beginning with an AgeTech case study, implementing roadmapping and topic modeling techniques, a roadmapping workshop, and producing an AI-augmented roadmap. The third phase encompasses a second application and validation process, starting with a combination of topic modeling and RAG, integrating these technologies into strategic roadmapping processes, establishing evaluation procedures, conducting a detailed application in AgeTech, and concluding with cross-industry validation to demonstrate the broader applicability of the developed approach.

1.6. DOCUMENT STRUCTURE

The structure of this thesis consists of six self-contained chapters, each addressing distinct aspects of the research. Chapter 1 introduces the research problem, objectives, and design science research approach. Chapter 2 establishes the background knowledge through a systematic literature review employing bibliometrics and topic modeling techniques. Chapter 3 presents the first application in AgeTech, integrating roadmapping with topic modeling techniques, conducting a roadmapping workshop, and developing an initial AI-augmented roadmap. Chapter 4 details the second application and validation, focusing on the refined integration of topic modeling and RAG into strategic roadmapping processes, evaluation procedures, and cross-industry validation to demonstrate broader applicability. Chapter 5 synthesizes the research findings into prescriptive design principles for researchers and practitioners interested in implementing similar AI-augmented strategic planning approaches. The concluding Chapter 6 summarizes the contributions, addresses limitations, and proposes directions for future research in AI-enhanced strategic roadmapping.

2. BACKGROUND: SYSTEMATIC LITERATURE REVIEW

2.1. FOCUS

A systematic review, in line with the PRISMA-P guidelines (Shamseer et al. 2015), examined the interlinkages among artificial intelligence and strategic planning, with a particular focus on digital roadmapping.

The latest review in Technology Forecasting and Social Change shows that the number of published papers on roadmapping has significantly increased over the past two decades, outpacing scenarios (Park 2020). A strategic roadmap is crucial for effectively communicating strategic intent and associated plans. More than just a communicative tool, the roadmap's structure, embodying various dimensions of a strategy, enhances the likelihood of successfully realizing strategic intentions (Kerr and Phaal 2022).

Strategic roadmapping applies a time-based and often graphical-based framework to develop, represent, and communicate strategic plans (Alcantara 2019), as seen in Figure 3. Therefore, Roadmapping is used to help organizations deal with complex and uncertain innovation challenges using simple, people-centric, collaborative, and multifunctional techniques (Oliveira, Routley, and Phaal 2022). Roadmapping is mainly divided into an expert-based approach emphasizing expertise to develop roadmaps and a computer-based approach using large textual databases for computer analyses (Kostoff 2001).

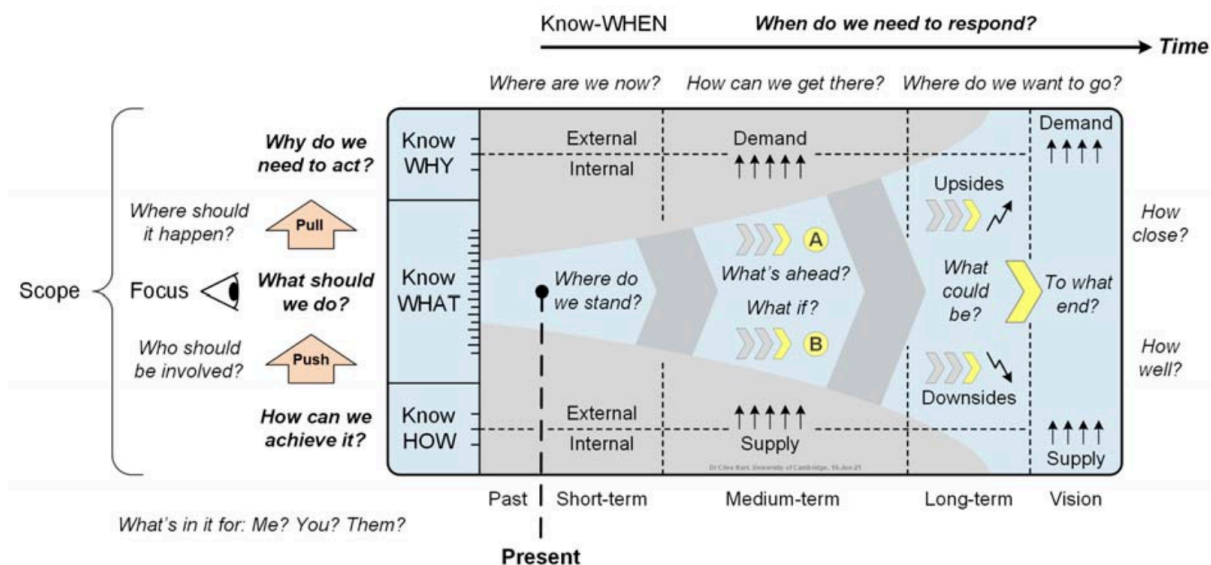


Fig. 3 Governing framework of roadmapping (Kerr and Phaal 2022)

A roadmap's condensed visual representation is instrumental in delivering a high-level, comprehensive overview of a system on a single page. Integrating all critical perspectives facilitates productive strategic discussions, consensus-building, and action alignment. Such a roadmap enables the holistic assessment and management of complex systems like businesses (Phaal 2007).

Roadmapping, in the same ways as other strategic planning techniques, has not emphasized the usage of data mining to build strategic plans (Eroglu and Kilic 2017), focusing primarily on the expert-based approach. Today, roadmapping faces the challenge of presenting a substantial and intricate amount of data in a format that is easy to comprehend, all while ensuring that it remains pertinent to the target audience (Kerr and Phaal 2022).

Therefore, roadmapping combines expertise and computational analysis to craft strategic plans, traditionally favoring expert-driven methods. However, the advent of digital roadmapping has expanded its capabilities immensely. By harnessing AI and machine learning for data assimilation, analysis, and rapid strategy iteration, digital roadmapping enhances adaptability and precision in strategic decision-making. This digital transformation enables more accurate assimilation of large amounts of complex data within an easy-to-understand visual framework, potentially contributing to improved organizational performance.

In roadmapping digitalization, four key areas demand attention: strategy formulation, landscaping, social interaction, and information management (Oliveira et al. 2023), as illustrated in Figure 4.



Fig. 4 The four dimensions of roadmapping digitalization (Oliveira et al. 2023)

Firstly, analyzing the expert-based links in the roadmapping process is essential when discussing strategy formulation. Then, it is crucial to see how digital tools are introduced for topic connections, multilayer links, and defining strategic narratives and priorities.

Landscaping, another aspect of the roadmap, starts with people-centric brainstorming, followed by applying descriptive tools to gather supplementary information. Predictive tools then come into play to envisage potential topics, while prescriptive tools can aid in strategy formulation.

When looking at social interaction in the roadmapping process, it is critical to determine if there is collocated interaction with analog information or if there is digitized information in the roadmapping process. Beyond that, social interaction can be driven by remote interaction using digital information or even virtualized interaction with digital people and information in roadmapping.

When discussing digital information management in the roadmapping process, analog information can be employed in the roadmapping process, or native digital information can be utilized. Further, along the process, digital information is not just utilized but also managed. Lastly, the process can integrate and update digital information in roadmapping (Oliveira et al. 2023).

Investigating the relationship between roadmapping digitalization and performance necessitates understanding the roadmapping context and data utilization. The former includes contemplating the organizational context, team experience, and the maturity of roadmapping implementation. To explore maturity, we refer to a model that navigates roadmapping implementation premised on extensive primary and secondary data analysis. This model gauges whether the organization has initiated roadmapping for strategic planning, has committed to its use, has trained its team, has developed and used roadmaps within specific departments, and finally, whether roadmapping activities are seamlessly integrated across the organization (Hirose et al. 2020).

Meanwhile, data application to the roadmapping process can be categorized into three approaches: supporting traditional roadmapping, mediating market wants and technological innovations, and aggregating value to the roadmapping process (Han 2022).

Beyond that, the roadmapping framework's visual aspects play an essential role. One crucial aspect is the visual nature of the roadmap framework, how it reveals patterns in the evidence and potential gaps in the evidence deserving further attention (O'Sullivan et al. 2021). Moreover, the roadmapping framework's visual nature can involve the participants' imagination, inspire motivation and identification with the roadmap, and be considered suited for convincing communication and presentation purposes (Eppler and Platts 2009).

Roadmapping performance is linked with several critical factors within an organization. One aspect is understanding the importance of knowledge diffusion related to roadmapping among team members. Another focus attribute is ensuring that decision-making tied to the roadmapping process is not unilateral but built on collective consensus. Emphasizing expertise in managing information throughout the roadmapping implementation signifies efficient workflow. This capability extends to the roadmapping process, where tasks are effectively prioritized, leading to better decision-making. Suppose the effectiveness of the roadmapping process further manifests in the significant productivity demonstrated within the organization if the roadmapping process is highly agile. An additional noticeable feature is the active engagement of all participants throughout the roadmapping implementation process, and lastly, if the roadmap adheres to the highest quality standards (Oliveira et al. 2023). The connections between these concepts can be seen in Figure 5.

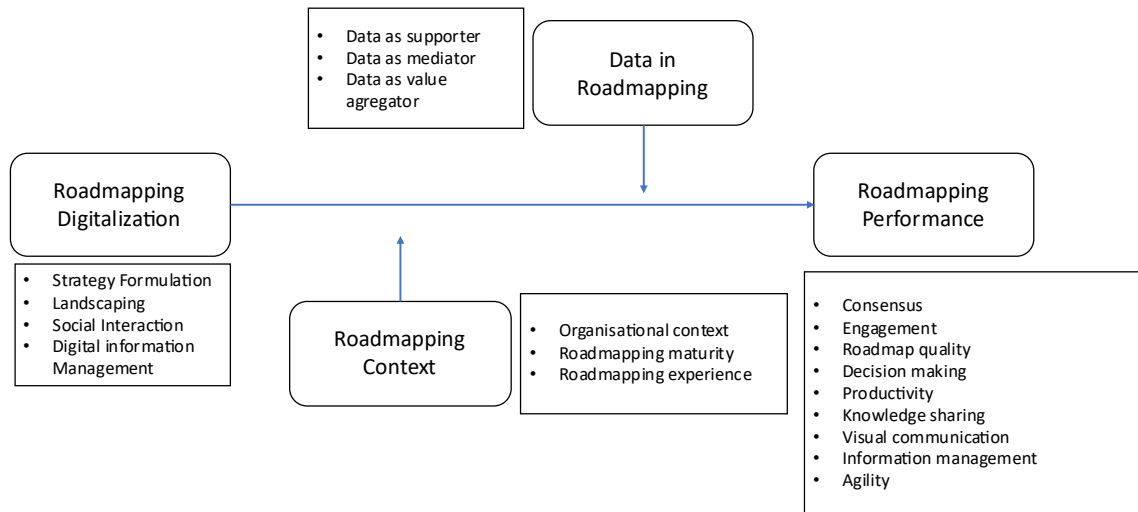


Fig. 5 Roadmapping digitalization relationship with roadmapping performance.

2.2. METHOD

This study was carried out in four stages, following the PRISMA-P guidelines (Shamseer et al. 2015). The primary stage aimed at collecting the research papers. The second stage consisted of a historical analysis. The third stage involved bibliometric methods applied to gain a deeper understanding of the research topics explored within these documents. The fourth stage encompassed neural topic modeling techniques for improved text comprehension and content analysis, which included classifying the papers' objectives, methodologies, and data sources, followed by further clustering using large language models and expert evaluation.

2.2.1. SYSTEMATIC REVIEW DATA COLLECTION

The present study uses bibliometrics focused on co-word analysis, which considers words frequently occurring together as having a thematic relationship. Two publications are connected when they co-occur in the "author keywords", "article titles", or "abstracts" (Donthu et al. 2021). This study produced a systematic review using the Web of Science and Scopus databases. The keywords chosen were: ("strategic management" OR "strategic planning" OR "organizational

strategy" OR "corporate strategy" OR "scenario planning" OR "roadmapping") AND ("artificial intelligence" OR "machine learning" OR "neural network*" OR "deep learning" OR "data mining" OR "text mining" OR "natural language processing" OR "natural language understanding" OR "big data" OR "analytics").

Three experts in strategy research chose these keywords for strategic planning to find studies that connect the current developments in artificial intelligence with strategy. In Web of Science, the research was done in topics limited to the research areas: Engineering; Business economics; Operations research & management science; Social sciences, and other topics. The results were limited up to 2022, finding 485 studies. In Scopus, the research was done in the article title, abstract, and keywords, limiting the research to articles and the research areas: Engineering; Business management, accounting; and Social sciences. The results were limited up to 2022, finding 978 studies.

These results were combined, and duplicates were removed using two techniques. First, the function mergeDbSources from the bibliometrix package in R combined the data sources, yielding 1247 studies. The levenshteinSim function was used to compare titles with minor differences in the databases that refer to the same articles, yielding 1236 unique studies.

The three experts read the titles and abstracts of these studies and selected 90 papers. The texts were read, leading to a final selection of 57 studies focusing on artificial intelligence applied in strategic planning. Therefore, articles that dealt with marketing, operations, and manufacturing strategies—i.e., functionally specific strategies—were excluded. Beyond that, there was a significant reduction in the number of articles when deleting reviews from the analysis. The reviews were deleted since the focus was on choosing articles that used artificial intelligence or exploring how artificial intelligence is used in the practice of strategizing. The reduction in articles resulted from these choices, focusing on only maintaining articles directly related to strategic planning and the utilization of artificial intelligence.

Thence, a rigorous snowballing process was conducted that used Citationchaser (Haddaway, Grainger, and Gray 2022), a method of snowballing that considers all references and cited articles based upon the website Lens.org that tracks the databases of Microsoft Academic Graph (MAG), CrossRef, CORE, PubMed, and PubMedCentral. From this snowballing process, 1823 references were found, and 1715 cited articles. The titles were read from these articles,

leading to a selection of another 37 studies. Then, the texts were read, leading to a final selection of 11 extra studies. When the keyword search and snowballing process results were combined, 68 studies were selected for this literature review.

2.2.2. HISTORICAL ANALYSIS

A comprehensive historical analysis was conducted, which involved an exhaustive review of scientific articles by a subject matter expert. This step entailed an in-depth reading and understanding of all the selected articles to accurately depict the chronological development and the evolution of themes and methodologies over time. Each article was meticulously scrutinized, and the salient information, findings, and conclusions were detailed and categorized concerning their historical context. This methodical process provided a holistic understanding of how the research field has unfolded and progressed historically, capturing the essence of each piece of scholarly work in the context of the evolving research landscape.

2.2.3. BIBLIOMETRIC DATA ANALYSIS

The bibliometrix R-package was used, along with VOSviewer. The bibliometrix package was used to do all the analysis, while VOSviewer was used with the bibliometrix package to generate the visualizations, specifically the networks.

A co-word analysis was applied, drawing the conceptual structure of a field using a word co-occurrence network to map and cluster terms extracted from keywords, abstracts, and other bibliometric resources. Then, the co-word analysis focuses on the most important words and keywords of documents to study the conceptual structure of a research field (Callon 1983), producing semantic maps of a field that help to understand its cognitive structure (e.g. Donthu et al. 2022). We have created a co-word analysis in which the item's weight determines the circle's size. The higher the weight, the larger the circle will be. Beyond that, the distance between the keywords in the visualization indicates the relatedness regarding co-occurrence links (Perianes-Rodriguez, Waltman, and van Eck 2016).

2.2.4. TOPIC MODELING ANALYSIS AND CONTENT ANALYSIS

2.2.4.1. TOPIC MODELING ANALYSIS

The documents were converted from PDF to TXT format using ABBYY FineReader. This database was further inspected using LDA, which extracts topics and keywords from documents based on word distributions and considers the relationships between words and contexts. We utilized NLTK, Spacy, and Gensim libraries in Python to conduct our analysis. The NLTK and Spacy libraries were used to convert the text to lowercase, remove stop words, perform lemmatization, select nouns, adverbs, adjectives, pronouns, and verbs for analysis, and finally, prepare the words for the LDA analysis conducted using the Gensim library. An important consideration when constructing an LDA analysis is choosing the number of clusters to be studied.

We constructed a table comparing the coherence score, which measures how understandable the topic formation is and the number of topics. From that, we chose six topics because they provide many topics and are within a threshold in coherence scores, as seen in Figure 6.

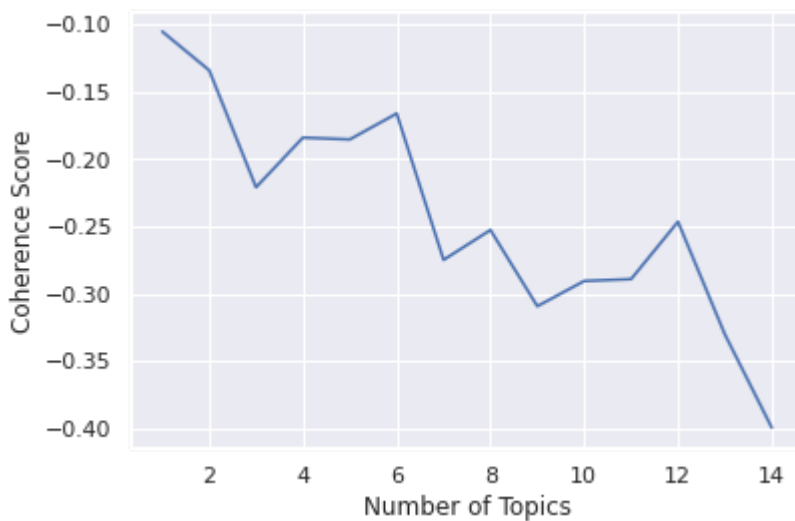


Fig. 6 Coherence scores.

This database was further inspected using neural topic modeling to extract topics contained in the texts. The documents were segmented into sentences using the Spacy library, resulting in 17513 sentences. Sentence clustering was performed using BERTopic.

BERTopic leverages clustering methodologies and a class-based variation of Term Frequency-Inverse Document Frequency (TF-IDF) to generate coherent topic representations. This model is organized into three distinct phases: first, generating document embeddings utilizing pre-trained language models; second, diminishing the dimensionality of these embeddings to construct clusters of semantically similar documents; and third, devising a class-based variant of TF-IDF to extract topic representation from each identified topic. The versatility of this structure enables BERTopic's application across a broad spectrum of scenarios (Grootendorst 2022).

When generating the representative keywords for the topics, stop words were removed using the English words list from the Natural Language Toolkit (NLTK) (Loper and Bird 2002). Then, the ChatGPT API, GPT-4 (OpenAI 2023), generated labels for these topics, guided by a prompt, considering the keywords and representative documents extracted from BERTopic. The extraction of the topic label followed the format:

The topic is described by the following documents: [DOCUMENTS]
 The topic is described by the following keywords: [KEYWORDS]
 Based on the information above, giving a higher weight to the keywords, extract a concise topic label in the following format:
 topic: <topic label>

Of the original 74 topics, 48 more closely related to artificial intelligence in strategic planning were selected for further investigation.

2.2.4.2. CONTENT ANALYSIS

After the topic modeling, a comprehensive content analysis was undertaken, wherein all the articles were systematically reviewed and scrutinized by a subject matter expert. This extensive review process aimed at classifying the content of each article based on three major dimensions: the text's objectives, the methodology employed, and the data sources utilized. This was done using MAXQDA, after which the expert read the articles and classified part of them into the categories previously mentioned. MAXQDA is used to systematically analyze text (e.g. Castro et al. 2022; Trevisan et al. 2023), allowing researchers to mark and extract important text passages for further analysis. The instruments of data collection and the procedure of the research process

are fully disclosed, ensuring a comprehensive understanding for the study recipients (Rädiker and Kuckartz 2020).

Each text part was closely examined during this process to identify and categorize its alignment with the article's objectives. This process facilitated an understanding of the focal points of the research. Simultaneously, a detailed analysis of the methodologies employed in each research article was conducted. This involved an in-depth investigation into the research methods, techniques, and approaches adopted, enabling a thorough comprehension of the diverse methodologies prevalent in the research field. At the same time, an examination of the data sources leveraged in each article was carried out. This facet of the content analysis involved identifying and categorizing the variety of data sources drawn upon for the research studies. It provided an insight into the breadth and depth of data sources utilized across the research area, revealing the complexity and diversity inherent to the field.

The content analysis phase was completed using 68 sources to analyze the text's objectives. However, a subset of 59 sources was used to analyze the methodology and data sources. That was done because nine articles were considered theoretical, while 59 had empirical applications. After the objectives, methodologies, and data sources were extracted from MAXQDA, they were summarized using GPT-4 with the following prompt:

Summarize the following objectives (methodologies, data sources) from scientific articles:
[DOCUMENTS]

After the summarization process, topics were extracted from the objectives using GPT-4, with the following prompt:

Considering the following objectives extracted from 68 scientific articles related to management strategy, technology roadmapping, and artificial intelligence:

TEXT: [DOCUMENTS]

Separate the articles into a diverse range of themes, providing specific descriptions of these themes based on the objectives of the scientific articles.

While the topic modeling process yielded satisfying results regarding the identified thematic areas, the document allocation to these themes proved inadequate. This outcome necessitated manual intervention in the document clustering process. Drawing upon their extensive expertise and understanding of the subject matter, the researchers reassigned each document to the most appropriate topic. This manual refinement process was necessary to ensure a more accurate and insightful representation of the topics, providing a coherent categorization that aligns closely with the intrinsic content of the documents.

The process was likewise attempted using the methodologies and data sources used in the corpus of papers. However, given these components' unique specificity and technicality, automated clustering failed to produce satisfactory outcomes. Consequently, the researchers leveraged their expertise to classify the methodologies and data sources manually. This approach, rooted in expert knowledge, ensured an accurate clustering, contributing to a more robust and reliable analysis.

2.3. SYSTEMATIC REVIEW RESULTS

In the forthcoming sections, we will delve into the key findings garnered from our research. The results will be compartmentalized based on the various analytical methods employed during the study, which include historical analysis, bibliometric analysis, topic modeling analysis, and content analysis.

2.3.1. HISTORICAL ANALYSIS RESULTS

The earliest article in the data was an academic paper that aimed to summarize some surprising advancements in robotics and examine the implications of these developments for general management instead of production management. The paper laid the groundwork for the potential for a supercomputer to share or assume the functions of a corporate CEO (Holloway 1983). Following that, an article from 1986 explored the feasibility of offering artificial intelligence recommendations that were immediately practical and could be translated into hardware and software systems to support the strategic planning function. The authors described a basic software program on Organizational artificial intelligence (Orsini 1986). It shows that the desire and initial tools to use artificial intelligence in strategy began taking shape. However, the

research did not find articles that accomplished that in the next ten years, with articles written in 1997, 1998, 1999, and 2000.

The first discussed a new approach to scenario generation based on the theories of neural networks and truth value flow inference (TVFI) (Li 1997), showing the first mention in the articles of using artificial intelligence and neural networks in scenario generation. In the same year, another article presented a methodology for constructing distributed strategic planning systems and described ARISTOTE, a multi-agent planning support system designed to aid top-level managers in generating strategic scenarios and evaluating the feasibility and coherence of action plans (Pinson 1997). The next one introduced and described strategic planning in terms of its components and used an example to illustrate the application of strategic planning in the GSS setting. It further explored the utilization of AI-assisted categorization, in conjunction with facilitation and group participation, to enhance strategic planning (Orwig 1997). Other articles were focused on using artificial neural networks to support a diversification strategic planning approach (Udo 1998).

Meanwhile, the first emphasis on data mining came from a study that analyzed the constituent steps of the knowledge discovery process and the algorithms commonly used in data mining, arguing that information systems managers could apply these processes more effectively to achieve broader corporate strategies (Yoon 1999). Another article focused on modern decision aids and their integrated role in enhancing the strategic management process (Kostoff 1999). The final two articles from 1999 and 2000 discussed how neural network techniques can be used to imitate and replicate the process employed by managers in conducting strategy evaluations (Chien et al. 1999) and applying a backpropagation network, together with a searching algorithm, to assist in planning (Khong and Lim 2000). There is a gap in the literature, with new articles appearing only in 2006, showing that these techniques did not seem broadly applied and discussed academically.

From 2006 onwards, a continuous but low stream of articles was being written, with the most significant number of articles written in the 2020s. The publications resurfaced with a paper that studied the utilization of neural networks for forecasting performance (Wang 2006), followed by a paper that proposed a framework using adaptative neuro-fuzzy inference systems to construct rules to generate input-output pairs for strategy (Moayer 2009). Concurrently, other papers

searched for ways to create roadmaps to discover the business justifications and requirements to incorporate business intelligence in organizations (Ranjan 2008). In another endeavor, researchers uncovered the competitive advantage gained by data analytic tools (Klatt 2011).

The first papers in this review that discussed the use of roadmapping methodology based on quantitative data appeared in 2007, using text mining in documents to identify the morphology of existing products and technologies (Yoon 2007). Afterward, keyword-based product technology maps were created (Lee 2008). Other papers emphasized using patent information as a proxy to measure technological capabilities and build technology-driven roadmaps (Lee 2009). The number of papers connecting roadmapping with text mining and artificial intelligence increased yearly, with few papers published each year.

In the 2010s, citation network analysis was becoming more common, using computer-supporter forecasting methodologies (Kajikawa 2010), followed by papers that evaluated the statistical significance of scenarios suggested by algorithms (Bryant and Lempert 2010). Those developments led to a paper that suggested the phrase “data-driven roadmapping,” using techniques like association rule mining (Geum 2012) that were later used to identify the relationships between different roadmap layers (Geum 2015). One article proposed the creation of a subject-action-object, improving the keyword-based technology roadmapping approach (Choi et al. 2013). At the same time, another study identified data characteristics that can be used for roadmapping, focusing on data mining techniques and k-means clustering (Yoon and Phaal 2013).

Concurrently, papers started combining scientometric and natural language processing methods to construct future-oriented technology roadmaps (Chunlei Ye and Lu Feng 2013). Another paper used the theory of inventive problem solving, using semantic TRIZ, to process term clumping results, finding patterns that can be applied to build strategic roadmaps (Zhang 2014), followed by later advancements (Feng 2020). Following the necessity to interpret and decide between clumping or clustering results, an article constructed K-means clustering and introduced similarity measures for topic relationship identification to explore the interaction among technology roadmap components (Zhang et al. 2016). Different authors developed supporting systems for technology roadmapping, using futuristic data and keyword-based visual analysis (Kim 2016). Another approach was the combination of qualitative and quantitative techniques, focusing on bibliometrics, to build what was coined as a TeknoRoadmap (Bildosola 2017). A final

development in data-driven roadmapping that surfaced before the 2020s was the search for a roadmap that can continuously learn from data, showing the possibility of such development (Pora 2018).

Meanwhile, another researcher explored strategy formulation frameworks based on clustering approaches (Hadighi 2013). Concurrently, researchers created models that formalize the participation of stakeholders in the abstract organizational processes, integrating information sources (Dalmau-Espert 2016) and exploring the use of association rule mining algorithms on educational data to create a strategy for student information systems (Onan, Bal, and Bayam 2016). Beyond that, feature subset selection and feature weighting algorithm were used to solve strategic decision-making problems (Eroglu and Kilic 2017) and describe systems perspectives where data serve in real-time.

Afterward, other data sources were starting to be explored, like Twitter (Li 2019), websites, and news for usage in foresight and decision-making (Kayser 2017). A different data source explored was 10-K reports (Hassan Zadeh and Jeyaraj 2018) and financial disclosures (Prollochs and Feuerriegel 2020). Furthermore, researchers were striving to create automatic methods of defining strategic plans using text mining algorithms, categorization, and clustering for unstructured textual information (Rojas 2018). It is clear then that the usage of artificial intelligence in management was being once more considered as capable of bringing about significant changes in strategy, as the earlier research from the 80s and 90s expected, with texts asking how artificial intelligence affects the practice of management itself (Ferras-Hernandez 2018), trying to determine how to measure and prioritize key performance indicator for strategic planning (Kiron and Schrage 2019), address the role of business analytics in supporting strategy (Kunc and O'Brien 2019) and business intelligence (Abai 2019), and combine artificial intelligence with human intelligence (Lichtenthaler 2020).

The highest number of artificial intelligence and data mining applications to strategy began in the 2020s. One study used quantitative techniques focused on continuing to use key indicators to help with the strategic process, using techniques capable of dealing with small datasets (Wang 2020). Meanwhile, research was done on clustering techniques in technical analysis, applying Latent Dirichlet Allocation (Vukanti 2021) and text similarity calculation (Zhang et al.2021). At the same time, there was a search to understand the relationship between artificial intelligence

adoption drivers and barriers using the total interpretive structural model (Kar, Kar, and Gupta 2021). Furthermore, there was a continuation in the research of fuzzy cognitive maps (Trujillo-Cabezas 2021) and the utilization of neural networks (Huang et al. 2021). Finally, artificial intelligence was explored to create a state of knowledge promptly available to the right people within the organization (Azzam and Beckmann 2022), creating a more robust mechanism to support strategic decision-making (Grande-Ramírez 2022) and a general emphasis on creating frameworks capable of predicting quantitative technological change (Kwon 2022).

Concurrently, several studies proposed different solutions to improve strategic roadmapping with data. One of those solutions was using fuzzy cognitive maps (Davis 2022) following a quantitative scenario development (Son, Kim, and Kim 2020). Others continued to apply scientometric and text mining techniques (Khademi et al. 2021), integrating topic modeling (Kim 2021), helping organizations digitally transform (Kayabay 2022), conducting roadmaps digitally (Piccirillo et al. 2022), and combining qualitative and quantitative approaches to think about the future (Trujillo-Cabezas 2022). One option that was explored was the creation of a data layer as an intermediate link for the creation of technology roadmaps (Han 2022). At the same time, studies were made about the development of semiautomated roadmapping (Pora 2022), an article that combined a diverse range of techniques used topic modeling and sentiment analysis, which was also explored by other studies (Miao 2022), and Bayesian networks, leading to the creation a data-driven roadmap that was later confirmed with experts (Jeong, Jang, and Yoon 2021). Beyond that, new natural language processing developments, like BERT and semantic analysis, were used to create technology and market layers of strategic roadmaps (Feng 2022). Several studies focused on the application of data-driven roadmapping to case studies (Miao 2022; Nazarenko 2022; Ozcan 2022).

From those analyses, it is clear that artificial intelligence has been increasingly applied in strategy and technology roadmaps, especially considering the increasing number of articles using deep learning through current natural language processing techniques. The latest developments involving BERT show greater attention to the state of the art of natural language processing and understanding; however, BERT is used to classify documents, not for clustering (Feng 2022). Meanwhile, LDA continues to be used in clustering problems (Hassan Zadeh and Jeyaraj 2018), showing the possibility of future studies to apply the latest developments in natural language

processing, like BERT and GPT-4, in clustering problems. This is especially true since clustering problems, at which point the most relevant topics from documents can be extracted without the necessity of previous biased inputs, are especially important for strategic development and the creation of technology roadmaps since they can go beyond the biases of experts and populate the layers of strategic roadmaps with structured information extracted from a large corpus of texts.

2.3.2. BIBLIOMETRIC ANALYSIS RESULTS

The documents analyzed cover the years 1983 to 2022. Over this approximately four-decade-long period, a total of 68 documents were sourced from 39 different scholarly outlets. Regarding the documents' impact, the average document age in the dataset is approximately 8.79 years. This includes a combination of seminal, older works and more recent publications. The average citation count per document is notable, at 24.59, indicating that the research in this field has had a considerable influence on subsequent studies. The cumulative references across all documents amount to 2941, highlighting the field's extensive academic dialogue and interconnectivity. This number implies the existence of a richly woven network of research, knowledge, and discourse. These results can be seen in Table 1.

Description	Results
Timespan	1983:2022
Sources (Journals, Books, etc.)	39
Documents	68
Annual Growth Rate %	7
Document Average Age	8.79
Average citations per doc	24.59
Average citations per year per doc	2.819
References	2941

Table 1 Main bibliometric results.

In Table 2, most documents were articles, with only six conference papers. Figure 7 shows

that the authors with the most articles were Yoon B., Park Y., and Geum Y., with four articles each. Table 3 shows that the source with the most citations was Technological Forecasting and Social Change, followed by IEEE Transactions on Engineering Management and Technology Analysis and Strategic Management. When considering the countries with the most citations, it can be seen in Figure 8 that it was South Korea, as expected, given that much development in computer-based roadmapping comes from the Korean school of thought (Park 2020), followed by the USA and China.

Description	Results
article	57
article; early access	3
article; proceedings paper	2
conference paper	6

Table 2 Types of papers.

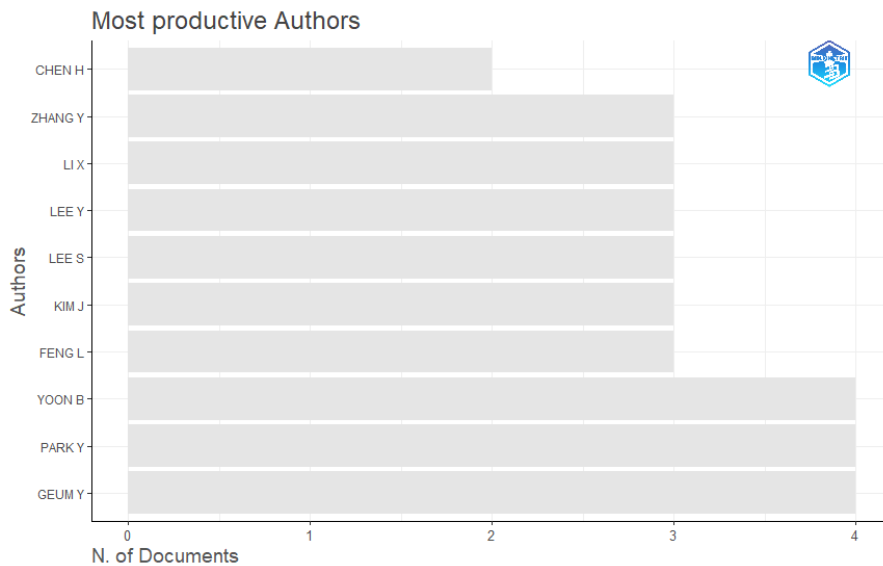


Fig. 7 Authors with the highest quantity of papers

Sources	Articles
TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE	12
IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT	5
TECHNOLOGY ANALYSIS \& STRATEGIC MANAGEMENT	5
APPLIED SCIENCES-BASEL	2
GROUP DECISION AND NEGOTIATION	2
IBERIAN CONFERENCE ON INFORMATION SYSTEMS AND TECHNOLOGIES CISTI	2
INTERNATIONAL JOURNAL OF COMPUTER APPLICATIONS IN TECHNOLOGY	2
JOURNAL OF BUSINESS STRATEGY	2
LONG RANGE PLANNING	2
R & D MANAGEMENT	2

Table 3 Sources of the papers.

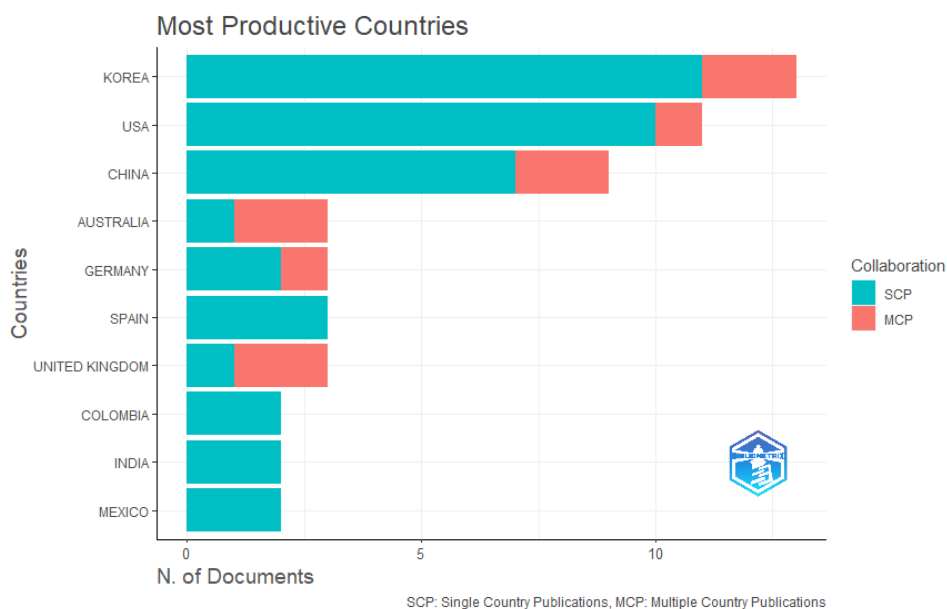


Fig. 8 Countries of the authors of the papers.

When considering the field's development throughout the years, Figure 9 shows that few articles were produced up until 2015. There has been a significant growth rate since, and the largest number of articles was produced in 2022, reflecting the recent developments in artificial intelligence.

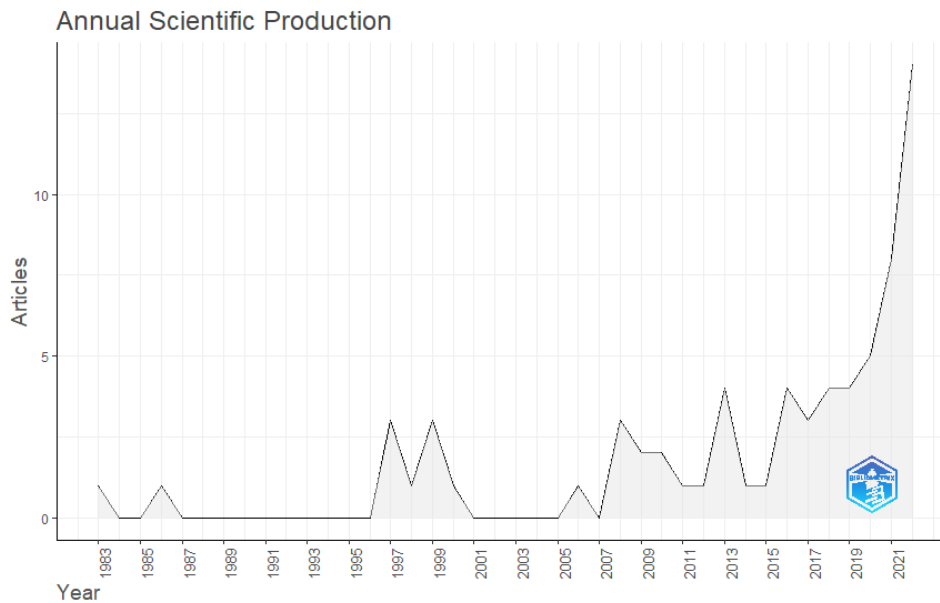


Fig. 9 Annual scientific production

The visual representation clarifies that the articles have many connections. That suggests that the authors of the articles cite one another, with articles more tightly packed in 4 clusters of colors: red, green, blue, and yellow. Two articles appear prominently within the map in Figure 10. The first is Phaal R. 2004, which reviews technology roadmapping in various organizational contexts (Phaal, Farrukh, and Probert 2004). The second one is Geum 2015, proposing an association rule mining (ARM)-based technology roadmap, offering a quantitative approach to identify interlayer relationships and develop keyword portfolios and relational maps, addressing the current limitations of subjectivity in traditional roadmapping (Geum 2015).

The author keywords presented in Table 4 show that the articles' selection represents the research's objectives, with the most cited keywords being the combination of technology roadmapping/roadmap, followed by text mining and strategic planning. A network was created in Figure 11. The keywords are divided into 6 clusters, with text mining at the center of the map and technology roadmapping occupying the center stage as well.

Firstly, the yellow cluster is focused on text mining, big data, and patents. The green cluster focuses on technology roadmapping, strategic planning, data science, and topic modeling. The blue cluster is focused on patent analysis, business, and emerging technology. Meanwhile, the purple cluster focuses on foresight and computational intelligence. The red cluster emphasizes strategic management, artificial intelligence, market research, and knowledge. Finally, the light blue cluster focuses on mining.

The keywords network lacks references to scenario planning, illustrating a more pronounced focus on roadmapping. Search terms tied to strategic concepts, such as organizational and corporate strategy, were also missing from the network. In addition to these, areas inherent to artificial intelligence—machine learning, neural networks, deep learning, natural language processing, and natural language understanding—were not featured in the keywords network.

Therefore, these networks show that artificial intelligence is less closely connected with technology roadmapping, having a distant connection to it that is mainly mediated by text mining. This shows the great potential of creating a closer connection between artificial intelligence and technology roadmapping and that text mining is a suitable medium for establishing this relationship.

Author Keywords	Articles
TEXT MINING	14
STRATEGIC PLANNING	10
TECHNOLOGY ROADMAP	9
TECHNOLOGY ROADMAPPING	9
ARTIFICIAL INTELLIGENCE	5
BUSINESS ANALYTICS	5
PATENT ANALYSIS	5
FORESIGHT	4
MINING	4
TRM	4

Table 4 Author Keywords.

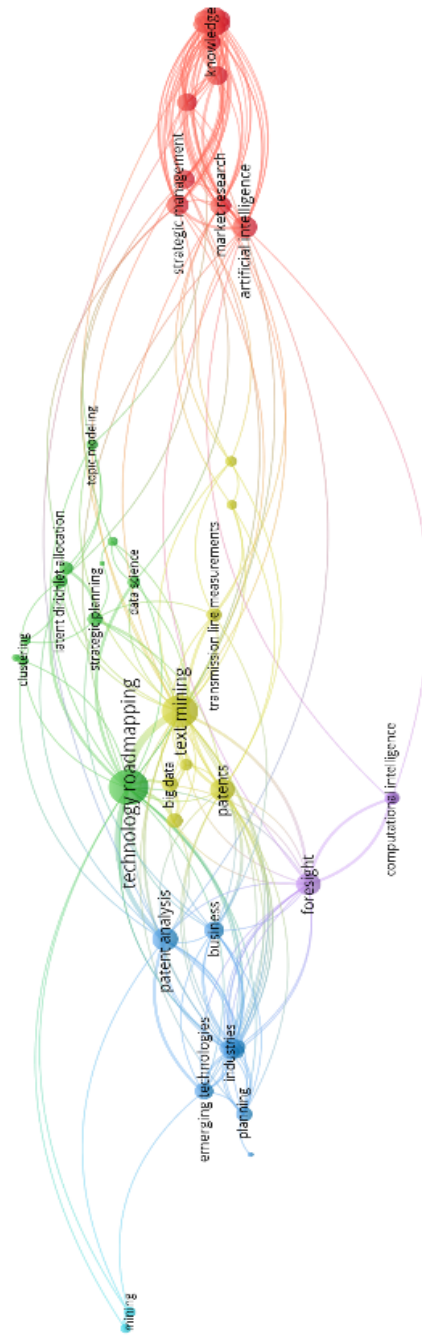


Fig. 11 Keywords network.

2.3.3. TOPIC MODELING ANALYSIS AND CONTENT ANALYSIS RESULTS

2.3.4. TOPIC MODELING ANALYSIS RESULTS

2.3.4.1. LDA RESULTS

Table 5 portrays a systematic analysis of topics derived from a corpus dealing with artificial intelligence, business strategy, and technology roadmapping. The topics are ordered by importance, reflected by the count, which denotes the frequency or relevance of each topic within the evaluated materials.

Count	Name	Keywords
18	Business strategy	"use" + "strategic" + "datum" + "business" + "strategy" + "system" + "management" + "process" + "information" + "analysis"
13	Data usage	"use" + "datum" + "research" + "cluster" + "method" + "base" + "number" + "network" + "analysis" + "value"
11	Technology roadmap	"technology" + "datum" + "process" + "use" + "product" + "roadmap" + "service" + "layer" + "market" + "data"
11	Technology patent	"technology" + "patent" + "product" + "analysis" + "base" + "use" + "technological" + "trm" + "development" + "map"
8	Technology scenario development	"Technology" + "topic" + "use" + "future" + "analysis" + "datum" + "scenario" + "process" + "development" + "change"
7	Business data	"process" + "use" + "cluster" + "factor" + "datum" + "organization" + "strategy" + "model" + "business" + "information"

Table 5 Topics extracted using LDA.

Starting at the top, the topic 'Business Strategy' is the most crucial theme. Its key concepts include strategic use of data, business strategy, system management, process management, and information analysis, among others. The high frequency suggests that the strategic application of data is becoming an integral part of businesses, playing a critical role in shaping system management, process management, and information analysis. It indicates the growing recognition

of data as a strategic asset, offering valuable insights for improving business strategies.

The next topic, 'Data usage', revolves around data, research, cluster methods, base number, network analysis, and value. It illustrates the increasing use of clustering techniques in data analysis, where similar data points are grouped to reveal hidden patterns or trends. The cluster method is essential in various fields, such as market segmentation and image analysis, allowing decision-makers to extract insightful conclusions from vast amounts of data.

Following are 'Technology Roadmap' and 'Technology Patent'. The 'Technology Roadmap' topic emphasizes data and processes in developing technology products, services, layers, and market data. It shows the strategic importance of technology roadmaps in guiding product development and market decisions. On the other hand, the 'Technology Patent' topic underscores the critical role of technology patents in analyzing product bases and uses, technological developments, and technology roadmapping. It suggests a significant focus on patent analysis to navigate the technological landscape and inform strategic decisions.

'Technology Scenario Development' highlights the key themes of technology, topic use, future analysis, data, scenarios, processes, development, and change. This topic reflects the trend of using technology scenarios in strategic planning. Technology scenarios enable organizations to visualize future situations driven by technological developments and changes, helping them anticipate potential opportunities and challenges. This forward-thinking approach can better equip organizations to adapt and thrive in an increasingly volatile and uncertain technological landscape.

Finally, the topic 'Business Data' centers around processes, cluster factors, data, organization strategy, modeling, business, and information. This topic suggests the rise of a data-driven business culture, where organizations leverage data to inform their strategies, drive decision-making, and optimize business models. The emphasis on cluster factors also suggests the growing popularity of cluster analysis in interpreting complex business data.

In conclusion, this analysis provides an overview of key trends at the intersection of AI, business strategy, and technology roadmapping. The high frequency of topics related to the strategic use of data, clustering methods, technology roadmaps, and technology patents signifies the growing importance of these areas in contemporary business practices. These insights can help stakeholders better understand the evolving dynamics in these fields and inform their strategic decisions.

2.3.4.2. BERTOPIC RESULTS

Table 6 offers a comprehensive analysis of various topics intersecting the fields of artificial intelligence (AI) and strategic planning. These topics are ranked in order of importance, denoted by the count column, which signifies the prevalence of each topic in the source material.

Count	Name
1359	Business Performance Analytics and Evaluation
866	Technology Roadmapping and Data-driven Development
536	Scenario Discovery in Decision Making
518	Organizational Knowledge in Complex Social Systems
482	Strategic Planning and Management
394	AI Adoption in Organizational Strategy
308	Emerging Technologies & Innovation Trends
298	Patent Analysis & Technological Advancements
291	Technology Roadmapping and Innovation Management
264	Agent Coordination & Blackboard Systems
248	Feature Subset Selection and Weighting Algorithms
237	Text Mining for Unstructured Data Analysis
222	Group Brainstorming Stages
203	Link Prediction in Networks
175	Twitter Sentiment Analysis on Emerging Technologies
175	Business Analytics in Strategic Decision-Making
173	Artificial Neural Networks and Learning Algorithms
164	BI Implementation and Analytics in Business Management

150	Latent Dirichlet Allocation in Topic Modeling
128	Artificial Intelligence Business Strategy
126	Keyword Extraction and Vector Construction
122	Hierarchical Clustering and Centroid Analysis
122	Phrase Frequency & Document Analysis
120	Data Mining Techniques and Applications
120	TISM Analysis - Drivers and Barriers
106	Keyword Mapping and Relationships
96	Citation Analysis & Bibliometrics
79	Organizational Goal-Factor Clustering for Departmental Strategies
73	Meta-Intelligence in Organizational Transformation
72	Data-Integrated Smart Service Systems
67	Big Data: Era, Challenges, and Opportunities
65	Patent Text Mining and Keyword Analysis
61	Layered Market, Product, and Technology Analysis
60	Morphological Analysis of Technology & Product Relationships
59	Determinants of Innovation Performance in Firms
59	Business and Social Media Strategy Alignment
59	Association Rule Mining Algorithms
54	LDA-based Topic Modeling
54	TRIZ Inventive Principles in Sparse Innovation
51	SAO Structures & Technology
48	Risk-Adaptive Technology Roadmap
48	Monitoring Roadmap Status & Impact of Key Driver Changes

47	Genetic Algorithm in Chromosome Optimization
45	Software Development & Network Integration in Pandemic
44	RS-MultiBoosting in ML Forecasting
39	Foresight in Future Exercises and Methods
38	AI Concept Categorizer Tool
36	Data Lifecycle Roadmapping Challenges

Table 6 Topics extracted using BERTopic.

The analysis identified 'Business Performance Analytics and Evaluation' as the most significant subject. This topic involves using data experts and specialized research to enhance business performance, underscoring the increasingly pivotal role of data analytics in modern business operations. It suggests that companies utilize data science to understand and improve performance, relying heavily on expert input and meticulous research.

'Technology Roadmapping and Data-driven Development' emerged as the second most important topic. This topic emphasizes the critical role of technology roadmaps in technology planning, particularly concerning data-driven approaches to development. The prevalence of this topic indicates that businesses are leveraging data-driven insights for future technology planning, which helps align their short-term and long-term strategic goals.

'Scenario Discovery in Decision Making' ranked third. This subject illustrates the increasing relevance of scenario-based methodologies in decision-making processes. It demonstrates that businesses utilize scenario planning and discovery techniques to anticipate future situations and make well-informed decisions.

'Organizational Knowledge in Complex Social Systems' and 'Strategic Planning and Management' underscore the significant focus on information management within complex social systems and the critical role of strategic planning in modern businesses. The high ranking of these topics shows that companies increasingly recognize the importance of effectively managing their knowledge assets and using them strategically to navigate complex social systems.

'AI Adoption in Organizational Strategy' and 'Emerging Technologies & Innovation Trends' both enjoy a substantial presence in the study. The former underscores the significance of

recognizing and overcoming barriers to AI adoption in businesses. At the same time, the latter accentuates the focus on staying abreast of the latest technological developments and innovation trends.

'Patent Analysis & Technological Advancements' and 'Technology Roadmapping and Innovation Management' highlight the crucial role of intellectual property and innovation management in business strategy. These topics imply that businesses invest considerable resources in patent analysis and technological advancements to gain competitive advantages and inform their technology roadmapping efforts.

Further down the list, topics such as 'Feature Subset Selection and Weighting Algorithms', 'Text Mining for Unstructured Data Analysis', 'Link Prediction in Networks', and 'Twitter Sentiment Analysis on Emerging Technologies' illustrate the considerable focus on AI and data science techniques. These topics suggest businesses are exploring various methodologies and algorithms to extract meaningful insights from data, including unstructured and social media data, to inform their decision-making processes.

Topics like 'Artificial Neural Networks and Learning Algorithms' and 'Latent Dirichlet Allocation in Topic Modeling' reflect the application of advanced AI and machine learning models in business analytics. Their relatively high occurrence points to the importance of these techniques in developing sophisticated data analysis tools and models.

'Business Analytics in Strategic Decision-Making' and 'BI Implementation and Analytics in Business Management' highlight the role of analytics in business strategy. These topics show the growing reliance on business analytics for strategic decision-making and the importance of implementing business intelligence systems in managing business operations.

The table also covers many other areas, including 'Keyword Extraction and Vector Construction', 'Hierarchical Clustering and Centroid Analysis', 'Phrase Frequency & Document Analysis, and 'Data Mining Techniques and Applications'. These topics underline the diverse applications of AI and data science in strategic planning.

Toward the lower end of the list, topics such as 'Data Lifecycle Roadmapping Challenges', 'AI Concept Categorizer Tool', and 'Foresight in Future Exercises and Methods' hint at some emerging focus areas. These topics suggest that businesses are grappling with the challenges of integrating AI into business strategy, requiring a future-oriented approach to anticipate and

manage possible issues.

In conclusion, the analysis provides a comprehensive overview of the current trends and focal points at the intersection of AI business strategy. It significantly emphasizes data-driven decision-making, strategic planning, AI adoption, and technological innovation, all key factors shaping business performance and decision-making processes. This synthesis is particularly beneficial for stakeholders seeking to understand the evolving landscape of AI integration in business strategy and technology planning.

2.3.4.3. CONTENT ANALYSIS RESULTS

Figure 12 outlines various data sources used in scientific articles centered around artificial intelligence, business strategy, and technology roadmapping. The frequency count signifies the number of articles that utilized each data source.

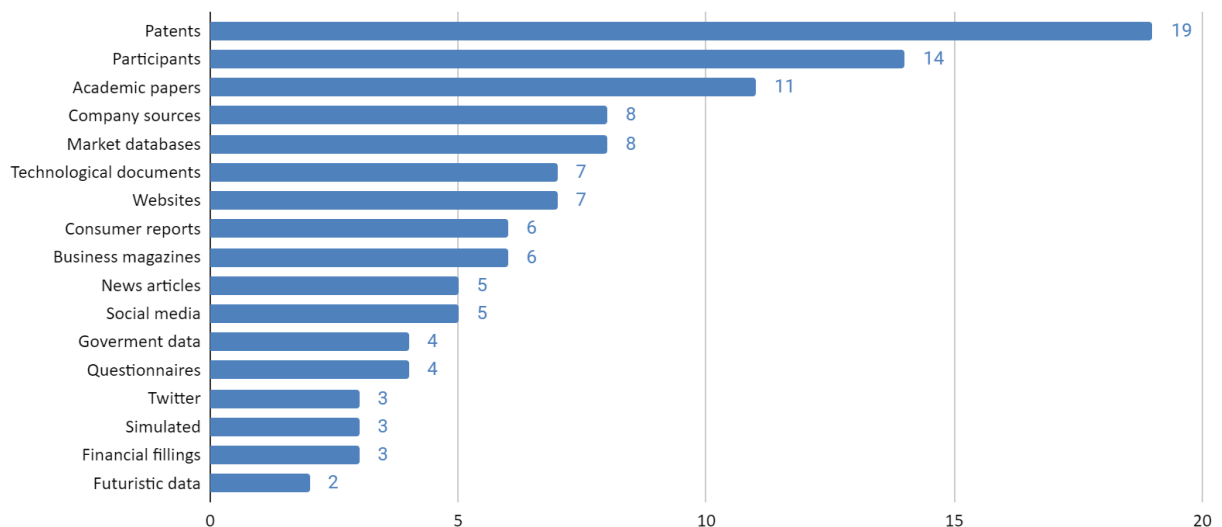


Fig. 12 Data sources used in the papers.

Leading the list with 19 instances are 'Patents', indicating that patent documents are a critical data source for researchers in these fields. Patents provide detailed technological and legal information about new inventions, offering insights into the direction of technological innovation and advancement. Next, with 14 instances, are 'Participants'. This suggests a significant use of primary data collection methods, such as interviews or focus groups, where direct interaction with individuals or groups yields valuable insights.

'Academic papers' are cited in 11 instances, highlighting the importance of scholarly articles as a source of theoretical and empirical insights in these research fields. 'Company sources' and 'Market databases' have been used in 8 instances, underscoring their value in providing specific and often exclusive business or market-related information. 'Technological documents' and 'Websites' have been referenced seven times each, which suggests that online sources and technical documents are frequently relied upon to gather data.

'Consumer reports' and 'Business magazines' are referred to in 6 instances each, showing their relevance in offering industry trends, consumer behavior data, and business news. 'News articles' and 'Social media' have been used five times each, pointing to the importance of these platforms in providing up-to-date information and understanding public sentiment.

'Government data' and 'Questionnaires' are each cited in 4 articles, showing the use of public data and direct surveys in the research process. 'Twitter', 'Simulated data', and 'Financial filings' appear three times each, hinting at the variety of data sources researchers draw upon to suit their specific needs. 'Futuristic data' is used twice, which could involve forecasting or speculative data, emphasizing the forward-looking nature in these areas.

In conclusion, the analysis underscores the diversity of data sources in scientific research on artificial intelligence and strategic planning, ranging from traditional academic resources to novel digital platforms. This wide array of sources reflects these research fields' multidisciplinary and dynamic nature.

Figures 13-16 present AI-integrated methods employed in strategic planning research, organized into four distinct categories based on their analytical purposes and characteristics. Figure 13 displays text representation and vectorization methods that transform textual data into numerical formats. Figure 14 shows clustering and pattern discovery methods that identify hidden structures and relationships in data. Figure 15 presents AI-driven methods that apply advanced AI techniques for insights. Figure 16 illustrates domain-specific and mining methods that provide specialized analytical capabilities. The frequency counts indicate the number of articles employing each method within the analyzed corpus of 68 studies.

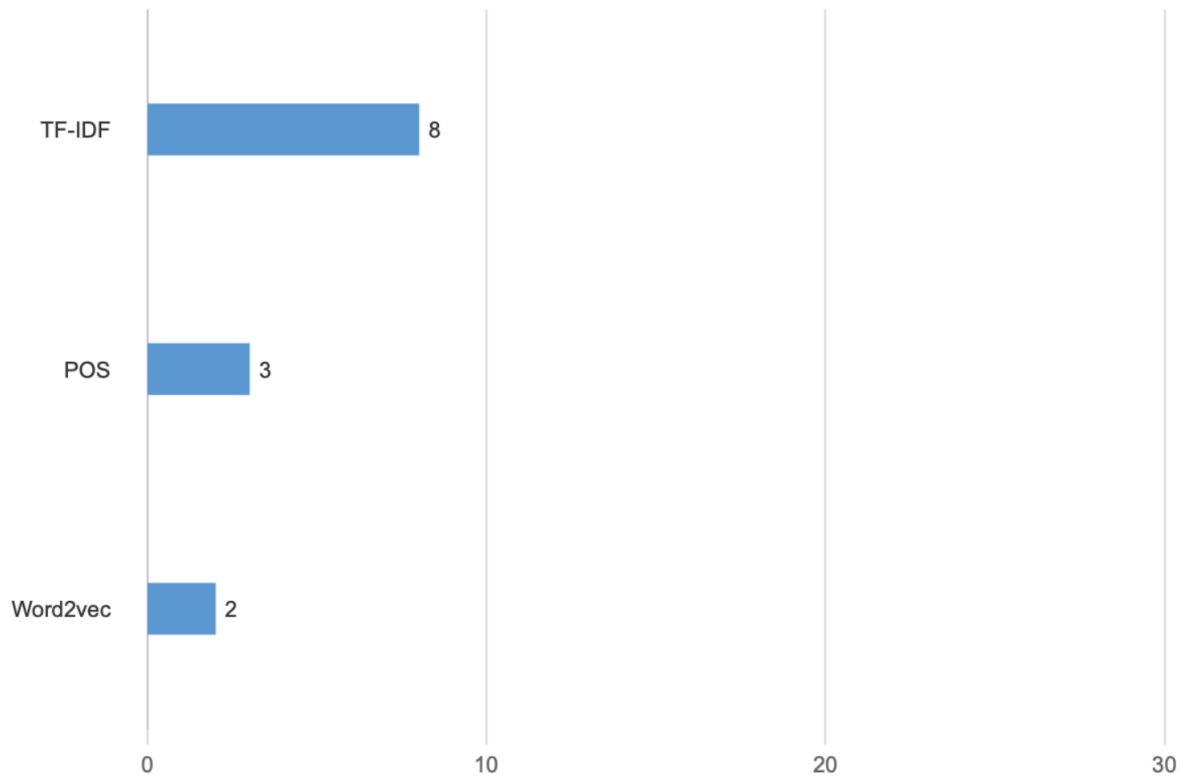


Fig. 13 Text representation and vectorization Methods

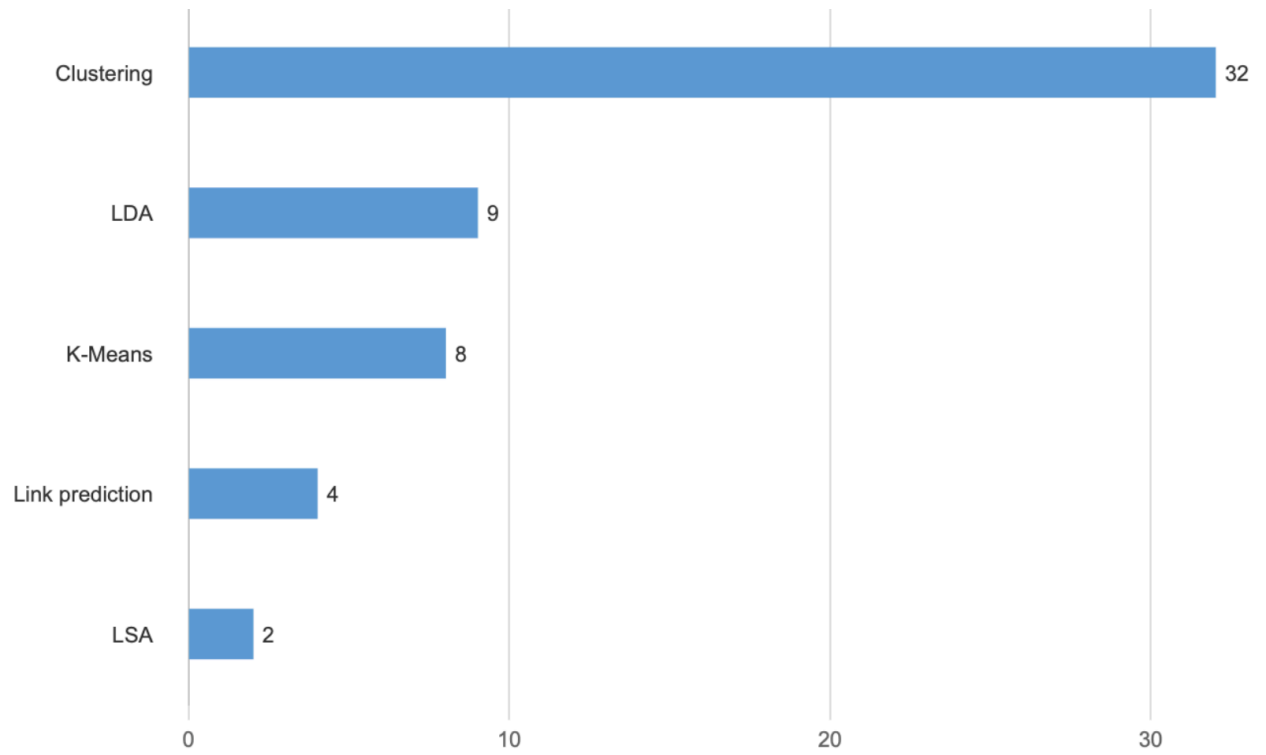


Fig. 14 Clustering and link analysis methods

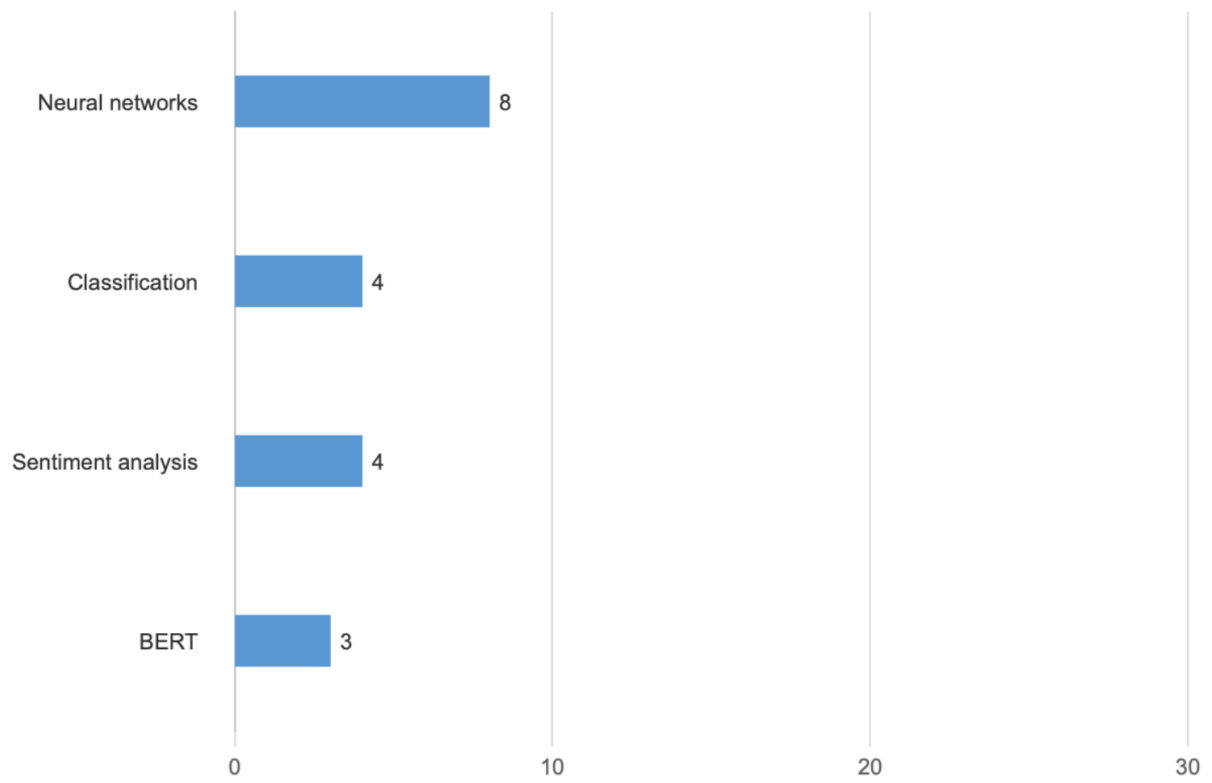


Fig. 15 AI-driven methods

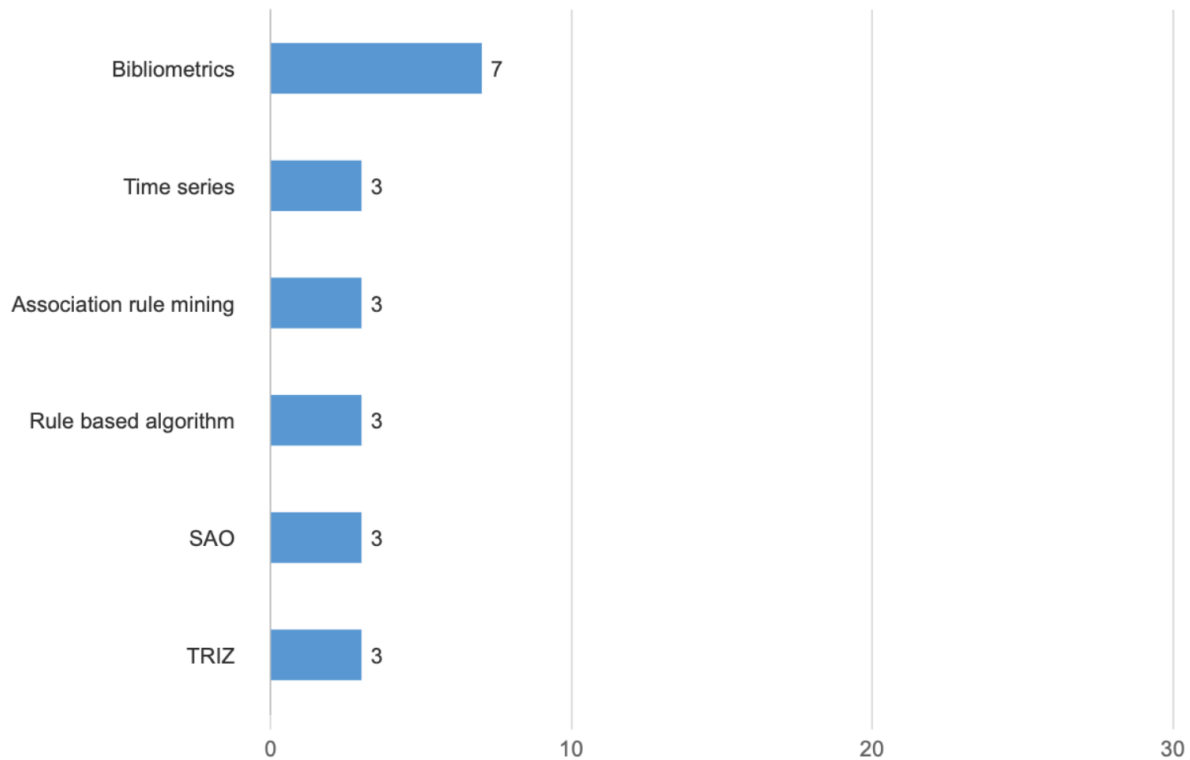


Fig. 16 Domain-specific and mining methods

As indicated by 32 instances, the most frequently used method is 'Clustering'. This technique is widely used in data analysis to identify and group similar data points, making it invaluable in these complex and multidimensional fields. Latent Dirichlet Allocation (LDA), a popular method for topic modeling, follows with nine uses. This signifies its prominence in discovering hidden semantic structures in text data, which can be particularly useful in AI and business strategy research.

TF-IDF (Term Frequency-Inverse Document Frequency) and K-Means appear eight times and are other standard methods employed. The former is an information retrieval technique that weighs a keyword's importance, while the latter is a cluster analysis method used to partition data into clusters. Neural networks, another critical method used in 8 instances, point to the increasing importance of deep learning models in handling complex tasks related to AI and strategic business decision-making.

Bibliometrics, used in 7 cases, indicates the relevance of this technique in measuring the

impact of academic publications, providing insights into research trends and directions. Other methods like Link Prediction, Classification, and Sentiment Analysis appear less frequently (4 times each), demonstrating their specific applications in predicting relationships, categorizing data, and understanding public sentiment.

BERT, Rule-Based Algorithm, SAO, POS, and TRIZ appear three times each, pointing towards their specialized uses in language understanding, creating structured algorithms, processing knowledge, analyzing linguistic components, and fostering innovative solutions, respectively. Methods like Association Rule Mining, Time Series, LSA, and Word2Vec have also found their place in the list, showing various techniques leveraged in AI, business strategy, and technology roadmapping. In conclusion, the analysis highlights the diverse array of methods used in scientific research in these areas, reflecting the complexity and multifaceted nature of the topics.

Table 7 categorizes scientific articles related to artificial intelligence, business strategy, and technology roadmapping, sorted into distinct topics with the corresponding number of articles belonging to each.

Topics	Number of articles
Technology Roadmapping: Developing and enhancing technology roadmapping methodologies, frameworks, and tools for various industries and contexts, including data-driven roadmapping, scenario-based roadmapping, and integration with other techniques such as text mining, natural language processing, and AI.	26
Forecasting, Scenario Planning, and Decision-making: Investigating and improving methodologies, techniques, and tools for forecasting, scenario planning, and strategic decision-making, including scenario discovery, Fuzzy Cognitive Maps (FCMs), and AI-assisted approaches.	15
Data Analytics and Strategy: Examining the role of data analytics, including text mining, cluster analysis, and machine learning algorithms, in supporting strategic planning and management, as well as alignment with organizational and social media strategies.	11
AI and Management: Exploring the role and impact of artificial intelligence on management practices, knowledge discovery, and decision-making processes within organizations.	8
Frameworks for Strategy Formulation: Proposing new frameworks and methodologies for strategy formulation, addressing aspects such as clustering, resource utilization, and stakeholder participation.	8

Table 7 Objectives of the papers divided into topics.

The most abundant topic with 26 articles is 'Technology Roadmapping'. This involves research into developing and enhancing technology roadmapping methodologies, frameworks, and tools for various industries and contexts. It includes data-driven roadmapping, scenario-based roadmapping, and integration with other techniques like text mining, natural language processing, and AI, reflecting the importance and prevalence of technology roadmapping in the contemporary digital landscape.

'Forecasting, Scenario Planning, and Decision-making' is the next most prolific topic,

covered in 15 articles. Research in this area focuses on investigating and improving methodologies, techniques, and tools for forecasting, scenario planning, and strategic decision-making, including scenario discovery, Fuzzy Cognitive Maps (FCMs), and AI-assisted approaches. This underscores the significance of advanced techniques in enhancing decision-making and planning in today's dynamic and complex business environments.

The topic 'data analytics and Strategy' has been examined in 11 articles. These papers delve into data analytics' role in supporting strategic planning and management and aligning with corporate and social media strategies, including text mining, cluster analysis, and machine learning algorithms. This emphasizes the increasing role of data analytics in shaping business strategy and ensuring alignment with various aspects of the organization. The topics 'AI and Management' and 'Frameworks for Strategy Formulation' appear in 8 articles. 'AI and Management' focuses on exploring the role and impact of artificial intelligence on management practices, knowledge discovery, and decision-making processes within organizations, highlighting the growing influence of AI on management. 'Frameworks for Strategy Formulation' proposes new frameworks and methodologies for strategy formulation, addressing aspects such as clustering, resource utilization, and stakeholder participation, underscoring the need for the continuous development of innovative strategies in business. In conclusion, the topics of these scientific articles reveal an emphasis on technology roadmapping, advanced decision-making methodologies, and the integration of AI and data analytics in shaping business strategies.

2.3.5. ANALYSIS OF SYSTEMATIC REVIEW RESULTS

The findings of this study corroborate the trends identified in previous research, where the use of intelligent systems for strategic decision-making and gaining a competitive advantage has been steadily increasing (Davenport 2016; Kiron and Schrage 2019; von Krogh 2018; Phan 2017). Similarly, the growth in the application of AI techniques in strategy formulation has been evident since the early 1980s (Holloway 1983; Orsini 1986). It has expanded recently, as demonstrated by the surge of publications since 2015. The surge in scholarly publications corresponds to the increasing focus on AI applications in unstructured environments (Di Ciccio 2014).

This analysis provides valuable insights into the growing intersection of these domains while reinforcing prior findings in the literature (Keding 2020). The discussion presented in this

study complements the recent advancements in technology, such as big data, self-learning algorithms, and powerful computing capabilities (Keding 2020; Mitchell 2019), which have been pivotal in AI's integration into various business processes.

Regarding the content analysis, the study's findings support the notion of the multifaceted nature of the research area, as several data sources (patents, academic papers, primary data) and analytical methods (clustering, LDA, neural networks) have been employed in the reviewed articles (Keding 2020). This diversity highlights the evolving nature of the research field, where various AI algorithms and techniques have been applied to different aspects of strategy formulation.

In line with the findings relating to applying LDA and BERTopic analysis, several studies discuss the growing relevance of AI, data analytics, and machine learning in modern business operations (Agrawal et al. 2017; Keding 2020). The discussion's findings derived from BERTopic modeling, which demonstrates the wide range of thematic areas being studied within the scope of AI, business strategy, and technology roadmapping, can also be seen in the strategic roadmapping mention of the Seoul school's computer-based approach, which leverages vast textual databases (Lee 2005). This approach is closely related to using AI-driven methods, such as BERT and GPT-4, mentioned in the discussion, to extract relevant topics from textual data.

Moreover, the discussion cites prominent themes in the BERTopic analysis that center around the increasing use of data analytics and AI-driven methods in strategic planning and decision-making processes. This converges with existing literature on the business potential of AI (Lee 2018; Phan 2017) and the capacity of AI in decision-making to mitigate data overload (Keding 2020).

The historical analysis emphasized the expanding interest in AI applications in strategy formulation and technology roadmapping, which is consistent with previous research highlighting the potential of AI in strategic management (Keding 2020). This finding resonates with the review by Tkác and Verner (2016), who predict that artificial neural networks will draw more authors and offer novel business application opportunities. Also, it reveals the evolution and growing application of AI techniques and tools, from early explorations into using AI for strategic planning (Holloway 1983; Orsini 1986) to recent advances in natural language processing, deep learning, and state-of-the-art AI methods (Feng 2022).

The analysis emphasized the expanding interest in AI applications in strategy formulation and technology roadmapping, consistent with previous research highlighting the potential of AI in strategic management (Keding 2020). This finding resonates with the review by Tkác and Verner (2016), who predict that artificial neural networks will draw more authors and offer novel business application opportunities. Also, it reveals the evolution and growing application of AI techniques and tools, from early explorations into using AI for strategic planning (Holloway 1983; Orsini 1986) to recent advances in natural language processing, deep learning, and state-of-the-art AI methods (Feng 2022). This finding is corroborated by bibliometric analysis, which demonstrates an upward trend in the research field since the early 1980s and the increased focus on AI applications in strategy formulation and technology roadmapping.

Beyond that, these findings align with the increasing relevance of digital tools, highlighting the importance of harnessing the power of bibliometrics and integrating them into strategic roadmapping (Vishnevskiy 2015; Zhang 2013). The expert-based and computer-based approaches to roadmapping (Kostoff 2001; Park 2020) also reflect the multifaceted and evolving nature of research in this area, as highlighted by the discussion's content analysis. This observation aligns with the wide range of data sources, including patents, which have been identified as crucial components in the roadmapping process (Kerr and Phaal 2022).

Furthermore, the discussion highlights the potential implications of advanced AI-driven methodologies in various aspects of strategy formulation. This aligns with Ardito's (2019) call for more empirical research on the business value of big data and Keding's (2020) recommendation for future research to explore AI's role in reimagining business processes and organizational design.

Specifically, data-driven roadmapping approaches have shown immense potential for future research to explore state-of-the-art NLP techniques and clustering algorithms, such as BERT and GPT-4. As demonstrated by the BERTopic results, its application exhibits a wide range of thematic areas addressed in the field, illustrating AI's potential to augment traditional organizational assumptions (Huang 2019) and reshape managerial tasks (Agrawal et al. 2017).

Therefore, the application of topic modeling techniques, like BERTopic and GPT-4, has great potential to augment strategic roadmapping.¹

¹ To further analyse AI in roadmapping, an exploratory data gathering was done with roadmapping practitioners related to digital roadmapping, see appendix 1.

3. FIRST APPLICATION OF AI-AUGMENTED ROADMAPPING

As stated in the introduction, the artifact development and validation progressed through two distinct applications. The first application focused on the AgeTech domain, serving as an initial proof-of-concept for integrating topic modeling within strategic roadmapping. This implementation utilized BERTopic for clustering and AI-assisted topic labeling, demonstrating the feasibility of augmenting traditional roadmapping processes with AI topic extraction. In the following section, we justify the relevance of the AgeTech context for the purposes of this research. Then, we detail how the development and testing of the tool took place in this context.

3.1. WHY AGETECH?

Considering the recent developments of the computer-based approach, specifically topic modeling applications in strategic roadmapping, this study applies it to the real case scenario of an AgeTech organization. The field of AgeTech, which harnesses contemporary technologies for the betterment of the elderly population's well-being and care (Sixsmith 2022), necessitates strategic navigation of various technological developments and emerging trends to optimally serve its intended demographic. AgeTech focuses on sectors such as e-health, AI, machine learning, robotics, and mobile technologies and involves various facets such as disease management and daily routine activities (Lan Fang 2022; Sixsmith 2022). Incorporating data-driven roadmapping into the AgeTech field can help its efforts efficiently, aligning technological advancements with the needs of an aging population. Given the visually delineated overview roadmaps can provide, they would serve as guiding tools for inter-departmental synchronization, strategic direction setting, and proactive policymaking, fostering an effective framework for AgeTech organizations to operate in.

Indeed, the rapid rise in the world's elderly population has substantially fueled the development of these technologies for this demographic (Sixsmith 2022). This increase is not merely a demographic trend but an influential catalyst that propels the research and development in AgeTech, aligning it with the aging population's needs.

Furthermore, AgeTech has been a propagator of technological solutions designed to ameliorate older people's health, functional autonomy, and overall quality of life (Sixsmith 2022). The implementations conceived under its banner are manifold and extend to the conception of new

devices, products, and services. Together, these contribute towards legislation and policy inclusion across varied spheres, such as in-home care, community services, and broader service arenas (Sixsmith 2022). The horizon of AgeTech applications is far and wide: from bolstering social connectedness and well-being support to integrating mental health interventions and fostering a sense of interconnectedness for older individuals with their communities (Rubeis, Fang, and Sixsmith 2022).

Over the last few decades, there has been a significant growth in research and development directed towards aging and technology, considering the increase in the population that will necessitate assistance with daily life (Lan Fang 2022). AgeTech, therefore, allows us to reconstruct a narrative about aging that emphasizes the development of practical solutions in a socially equitable and just manner. It moves towards the tangible translation of those solutions into products and services that are both utilitarian and accessible for the elderly (Lan Fang 2022).

AgeTech, however, not only aims to assist older populations but also to instigate noticeable economic growth. The emergence of novel entrepreneurial opportunities spurs this growth, the alleviation of service burdens, and the enhancement of social and economic inclusion of older persons in society (Sixsmith 2022). Furthermore, it contributes towards reducing inequality and the impact of disability and cognitive decline. It minimizes potential vulnerabilities associated with aging and maximizes their economic and social values—for instance, by offering improved educational and work-related opportunities (Sixsmith 2022). Thus, the expansive scope of AgeTech extends beyond merely meeting the needs of an aging population and progresses towards augmenting their societal contribution.

Henceforth, the evolution and rise of an increasingly aging world population requires AgeTech, as a cross-disciplinary field, to adopt approaches that mitigate uncertainty and complexity. Especially as the impact of AgeTech is not just confined to individual well-being. Still, it extends to broader economic and societal implications (Sixsmith 2022); leveraging data-driven roadmapping can enhance strategic planning capabilities and enable more accurate forecasting of technological trends and their implementation (Kerr and Phaal 2022; Oliveira et al. 2022). This would assist AgeTech organizations in managing the intricate balance between utilizing emerging technologies and meeting the specific needs of aging populations. Furthermore, as roadmapping techniques evolve to incorporate digital tools and data mining methods (Park 2020; Eroglu and

Kilic 2017), AgeTech, which is inherently tech-oriented, can reap the benefits of integrating workshops and topic modeling in strategic roadmapping, thereby driving innovation and technology development synchrony with their strategic plans.

3.2. THE APPLICATION

The first application of our methodology produced an augmented strategic roadmap using scientific articles extracted from the Scopus database. For this implementation, we focused on the AgeTech domain. Three domain experts collaborated to develop the search query: TITLE-ABS-KEY((elder OR old* OR "late adulthood") AND (health) AND (technolog* OR tech OR automation OR robot) OR (AgeTech)) AND PUBYEAR > 2017 AND PUBYEAR < 2023 AND (LIMIT-TO(DOCTYPE,"ar")).

This search targeted articles published between 2017 and 2022 that addressed technologies for elderly health. The query yielded 4,739 scientific papers, of which 4,720 were included in the analysis after excluding 19 papers that lacked abstracts in the Scopus database. This corpus of abstracts was the foundation for our initial topic modeling approach and subsequent roadmapping process, representing our first attempt at integrating computational topic extraction with strategic roadmapping in the AgeTech context. The steps are represented in Figure 17.

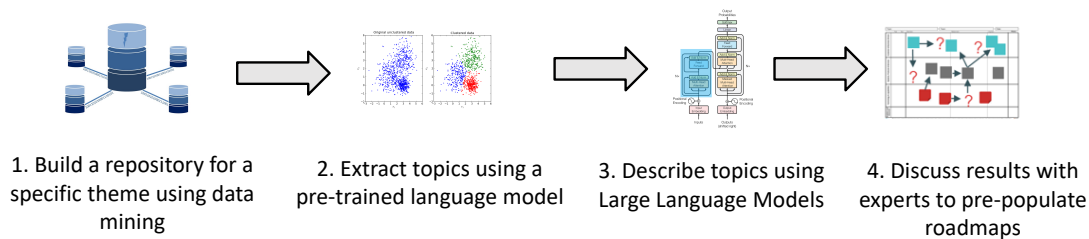


Fig. 17 Steps for AI augmented roadmapping

3.3. ROADMAPPING TOPIC MODELING

We used neural topic modeling to extract topics contained in the abstracts. The documents were segmented into sentences using the Spacy library, resulting in 80662 sentences. Sentence clustering was performed using BERTopic, which used the 'all-MiniLM-L6-v2' model for generating sentence embeddings due to its good performance and fast processing (SBERT.net 2023). The minimum topic size was 154 sentences, equivalent to approximately 0.002% of the total sentences. This led to 67 topics and one outlier topic, which comprised 37018 sentences. These outliers were not primarily associated with any specific topic. A high number of outliers is common when using BERTopic. Previous researchers have pointed out that it generates many outliers, which is a current algorithm limitation (Egger and Yu 2022). When generating the representative keywords for the topics, stopwords were removed using the English words list from the Natural Language Toolkit (NLTK) (Loper and Bird 2002). Then, the ChatGPT API, GPT-4, generated labels for these topics. Guided by a prompt considering the keywords and representative documents extracted from BERTopic. The extraction of the topic label followed the format:

I have topic that contains the following documents: [DOCUMENTS]
 The topic is described by the following keywords: [KEYWORDS]
 Based on the information above, giving a higher weight to the keywords, extract a concise topic label in the following format:
 topic: <topic label>

Of the original 67 topics, 38 were more closely related to AgeTech; this choice was made based on inputs from an expert, that choose topics uniquely related to the strategic context of an AgeTech company. Following this, the topics were considered in terms of the highest frequency of sentences, high frequency, medium frequency, and low frequency, with the respective thresholds of 1–9, 10–18, 19–27, and 28–38. These results were used to populate a pre-roadmap. Beyond that, the topics were associated based on cosine similarity, with the topics in the 0.01 percentile of closeness, containing more than a 0.5504984 cosine similarity score, considered to be connected. The topics were used as input into GPT-4 to generate a vision for AgeTech. This vision was created based upon a desire of one of the interviewees to have a summarized analysis of what the roadmap aimed for, made automatically using artificial intelligence. The vision was created with the following prompt:

Considering the following topics limited by triple quotes, based upon agetech, technological solutions related to health for old people:

[DOCUMENTS]

Create a vision for an insurance company related to the theme of agetech, technological solutions related to health for old people.

The topic modeling yielded 38 distinct topics that were subsequently incorporated into the pre-roadmap, spanning the market, product, and technology layers. On the other hand, the sublayers were structured by the researcher with the help of an expert. In addition to the 38 topics directly originating from the topic analysis, there were 12 more topics described directly using keywords derived from the topics modeling, and 10 topics the expert developed indirectly based upon the topics modeling results and the keywords that were the basis of the topics. The pre-roadmap can be seen in Figure 18.



Fig. 18 Pre-roadmap

Cards legend: ■ Analysis topic; ■ Topic keywords analysis; ■ Indirect topics of analysis

3.4. ROADMAPPING WORKSHOP

After the topic analysis, a pre-roadmap was created based on the topics. Firstly, the pre-roadmap was populated by the topics themselves. Secondly, an expert analyzed the keywords and chose the most meaningful ones to add to the pre-roadmap. Finally, the expert chose topics directly related to the keywords to add to the pre-roadmap. Beyond that, the researcher chose sublayers of the pre-roadmap with the help of an expert to group the topics derived from the quantitative analysis.

Following that, a workshop was done with a strategic leader in an AgeTech-related organization as part of their live strategic planning process. Firstly, it was communicated to the participant that a data-driven pre-roadmap was created. However, before using the new results, he initiated the roadmapping process with information from a previous strategic roadmap that had been constructed for the organization. When he finished populating one of the layers of the roadmap—market, product, and technology—he was shown the results from the topic analysis and decided if the topics should be included, where they should be included in terms of the strategic layers and sublayers and at what time frame. The interviewee determined the sublayers.

The strategic roadmap under examination encapsulates a comprehensive collection of 99 topics. Of this total, 30 were a direct outcome of in-depth topic analysis, 8 were extracted from key term investigations, 6 were the result of a thorough examination of these critical terms conducted by researchers, and 12 were brought forth from a preceding strategic roadmap, these were extracted from a roadmap that the company had already built previously and wished to use as the basis for the new roadmap. Interestingly, the interviewee was instrumental in identifying the remaining 43 topics. Consequently, this diversely sourced compilation illustrates the value of a multi-faceted approach in constructing an exhaustive strategic roadmap.

A closer inspection reveals that 44% of the topics forming the backbone of the strategic roadmap were derived from quantitative analysis, 30% directly from the topics analysis, 8% from the keywords that were the basis of the topics and 6% created based upon the topics and keywords. This underscores the integral role played by data-driven methodologies in guiding this strategic planning. A breakdown of topic sources provides further insights: 79% of the topics from the topic modeling results were used, which harnesses statistical techniques to reveal hidden thematic structures within the dataset. This compares with 66% utilization of keywords, typically more

simplistic and explicit content representations. Meanwhile, 60% of topics generated by the researchers, an approach that incorporates human expertise and data analysis, were included. As depicted in Figure 19, these proportions illustrate the multi-dimensional nature of our topic sourcing and underscore the significant contribution of computational techniques, such as topic modeling, in shaping our strategic roadmap.



Fig. 19 Strategic Roadmap

Cards legend: ■ Analysis topic; ■ Topic keywords analysis; ■ Indirect topics of analysis; ■ From previous roadmap; ■ Determined by the interviewee

The strategic roadmap encompasses an extensive array of topics from analyzing AgeTech. One salient issue is the 'Rising health costs'. This topic underscores the increasing financial strain healthcare systems around the globe are facing, particularly as the world grapples with an aging population. The topics then delve into more specific aspects of AgeTech. 'Video Telehealth for Older Adults', 'Telemonitoring', and 'Teleconsultation' illustrate the shift towards remote healthcare delivery models. These technologies can increase access to healthcare services, particularly for older individuals who may face mobility issues or live in remote areas. The

strategic roadmap also features a suite of digital infrastructure and systems such as 'Proprietary medical records', 'Exam Request Applications', 'Telemedicine systems', 'Blockchain Networks', and 'Data lake'. These systems underscore the digital transformation of health services and the importance of secure and efficient data management. Innovative applications like 'mHealth Smartphone Apps', 'Anti falling gadgets', 'Physical activities trackers', and 'Social Robots in Healthcare & Interaction for Older Adults' have come into focus. These technologies demonstrate the breadth of AgeTech solutions and reflect a trend toward personalized, patient-centered care.

Lastly, the strategic roadmap includes broader societal and industry trends, such as 'Focus on prevention', 'Health Techs protagonism', 'Consolidation of large hospital systems', and 'Change in age structure'. These trends suggest a shift from disease treatment to prevention, a growing role of health tech companies in healthcare delivery, increasing consolidation in the healthcare sector, and demographic changes that could affect healthcare demand and delivery. All of the topics can be seen in Appendix 3.

3.5. AI-AUGMENTED ROADMAPPING FIRST APPLICATION DISCUSSION

Through topic modeling, and strategic roadmapping, we have acquired a holistic understanding of the growth and future potential of AgeTech solutions. Our findings underscore pivotal issues like soaring health costs, uncertainty in regulations, an abundance of health misinformation, the misalignment of interests in the sector, and the impact of the pandemic on healthcare and society. All these factors illuminate the complexity of the challenges faced by healthcare systems in dealing with an aging population and underscore the need for prescient strategies to maneuver the rapidly changing regulatory landscape.

The AgeTech field is a perfect blend of diverse topics like e-health, artificial intelligence, machine learning, robotics, and mobile technologies, which function as the tech-based underpinning of AgeTech frameworks (Sixsmith 2022). Specific areas crucial for older adults' lives, such as disease management and basic day-to-day activities, have integrated these technologies into various facets.

Our strategic roadmap delves into discrete factors of AgeTech, highlighting the importance of healthcare delivery models, technology-enabled chronic condition management, digital infrastructure, systems, and innovative implementations. An additional consideration is the

broader social and industry trends that focus on prevention, the heightened role of health tech companies, and consolidation in the healthcare sector. AgeTech's contribution to this shift from disease treatment to proactive prevention cannot be overstated (Rubeis et al. 2022).

Overall, the research findings emphasize the importance of strategic planning and collaboration in driving innovation and progress in AgeTech. Considering that this study will contain some extent of imprecisions in predictions considering the dynamic nature of markets and technologies, by continually reassessing and refining the strategic roadmap based on emerging trends and insights, stakeholders can ensure they are well-positioned to meet the evolving needs of older adults and contribute to the advancement of AgeTech for the betterment of healthcare and society as a whole.

Looking closely at the implications and applications of AI and machine learning in strategy formulation and technology roadmapping, one can delve deeper into the nuances of these technology applications. As witnessed across numerous publications and studies cited (Geum 2012; Jeong et al. 2021; Yoon and Phaal 2013), these techniques have demonstrated significant potential in the extraction of key insights and relevant topics from large volumes of textual data.

Many promising opportunities emerge when exploring these methods, as they bear the potential to develop highly comprehensive strategic roadmaps. Significantly, the interest in AI techniques dates back to the early 1980s, showcasing a consistent application of AI in this area over time (Keding 2020), underscoring their potential to aid in formulating strategies for sectors like AgeTech.

The workshop participant provided feedback about how data mining and topic modeling techniques augmented the discussions revolving around the strategic planning for AgeTech. This participant perceived the dual benefits these methods highlighted—firstly, cultivating the emergence of contemporary topics that are integral to AgeTech's progress; and secondly, substantiating key issues that were already known and regarded as substantial within the realm of AgeTech, but were now bolstered through empirical data.

Furthermore, the participants appreciated the utility of these techniques in efficiently populating the strategic roadmaps. The implementation of topic modeling relieved the obligatory burden from the participants to formulate all potential topics independently. Instead, they could select from a multitude of relevant topics gleaned through the data-driven approach. This selection

process allowed them the flexibility to complement the resultant insights with additional topics, thereby broadening their perspectives. This potential for convergence of empirical data-based topics and insight-driven topics elucidated a robust, well-rounded strategy for AgeTech's advancement.

The efficiency of the data-driven strategy led to a streamlined workshop experience. Key discussion points could be honed rapidly due to the pre-population of roadmaps, showing an improvement relative to the extensive time traditionally required for their construction. Consequently, this approach optimized the use of expert insight by directing their focus towards strategic AgeTech discussions, thus demonstrating the effectiveness of quantitative analysis in the construction of strategic roadmaps.

These findings illuminate the potential of AI and machine learning in strategy formulation and technology roadmapping. While our first application successfully demonstrated how AI-augmented roadmapping streamlined workshops and optimized expert input, it revealed limitations in evidence depth and source connections. The topics were created using topics modeling, but the description of the topics was restricted to only the names and the references could not be easily checked by the strategists. This initial implementation provided the foundation for our second application, which incorporated retrieval-augmented generation (RAG) to create topic-based reports with supporting scientific references. The evolution from neural topic modeling to an integrated RAG approach enabled validation across multiple industries.

4. SECOND APPLICATION OF AI-AUGMENTED ROADMAPPING

A second enhanced application was developed based on insights from this initial implementation. This refined version incorporated retrieval-augmented generation (RAG) capabilities, producing topic-based reports with supporting scientific references. The improved artifact was reapplied to the AgeTech domain with greater depth and validated across 8 cases in multiple industries, demonstrating its utility as a strategic planning tool. This cross-industry validation confirmed the artifact's effectiveness beyond its original application context, establishing its value as an approach to AI-augmented strategic roadmapping.

Our second application built upon the initial AgeTech implementation by enhancing the methodology with more advanced natural language processing techniques, retrieval-augmented generation and a report with details related to each topic. This iteration introduced automated report generation, providing experts with comprehensive topic summaries and supporting scientific references. This was an enhancement from the previous application, that had only the names of the topics and no easy way for the strategists to check the references that supported the topics in a report-like structure. The approach was applied to AgeTech again as a primary case study and then expanded validation across multiple industries.

4.1. INFORMATIONAL SOURCES AND TEXTUAL PRE-PROCESSING

The textual data used for analysis were the titles and abstracts of the texts. The articles were extracted from the Scopus database, given that it offers a compelling platform due to its interdisciplinary scope, robust analytical tools, and comprehensive citation indexing (Okagbue and Teixeira Da Silva 2020; Zhu and Liu 2020). The keywords were selected by solution developers and business leaders, a total of 6 specialists were consulted to choose the keywords. These specialists were primarily consultants who worked with companies across multiple industries, facilitating the roadmapping workshops while this research focused on enhancing the pre-population phase that prepared topics for their sessions. Those keywords were further expanded by using a prompt engineered for such a purpose, using the API of GPT-4o. The prompt that was used to expand the selection of the experts can be found on GitHub (<https://github.com/DataGomes/ReportRAG>). When the experts considered the keywords satisfactory, a search was made in the Scopus database. The years searched ranged from the last 5

years to the last 20 years, depending upon the experts' choice. With the parameters of the search decided, all the articles were retrieved, and the titles and abstracts were used for the analysis.

Furthermore, a detailed example is provided to ensure transparency. This specific example case focuses on a leading healthcare provider for the elderly in Brazil, illustrating the methodology's applicability within the growing field of AgeTech. This AgeTech case study employed a targeted search strategy within the Scopus database using the following keywords: TITLE-ABS ((elder OR old OR "late adulthood" OR senior OR aging OR geriatric OR "older adults") AND (health OR "well-being" OR care OR healthcare OR wellness) AND (technology OR tech OR "digital health" OR automation OR robot OR AI OR "artificial intelligence" OR "machine learning" OR telemedicine OR eHealth) OR (agetech OR "age-tech" OR "ageing technology")) AND PUBYEAR > 2017 AND PUBYEAR < 2024 AND LANGUAGE ("English") AND (DOCTYPE ("ar") OR DOCTYPE ("re") OR DOCTYPE ("cp")). These keywords, selected by two domain experts, aimed to capture studies related to AgeTech within titles and abstracts, limited to articles, reviews, and conference papers published between 2018 and 2023. This initial search yielded 11,270 studies, further refined to 10,790 scientific texts by including only those with a title, abstract, and DOI.

Pre-processing the textual data involved cleaning, removing extraneous elements such as hyperlinks and special characters, and employing the 'ftfy' library (e.g. Kyrlov and Chaplynskyi 2023), for data normalization. The text was segmented into sentences to mitigate the risk of information loss in long input contexts (Liu et al. 2024). Sentence chunking was done using the Natural Language Toolkit (NLTK) (Loper and Bird 2002). An overlapping chunking methodology was adopted to ensure content coverage, in line with Bergman et al. (2023). Sentences were extracted in groups of three, overlapping the first and last sentences.

Furthermore, each sentence triplet was prepended with the corresponding title, drawing upon the work of Singh and Singh (2024), who advocated title-context integration to provide more informative input for generative language models. Subsequently, embeddings were generated for each text chunk utilizing the Voyageai embedding model (Ma 2023). This model was selected based on its demonstrated superior performance within the Massive Text Embedding Benchmark (MTEB) framework (Muennighoff et al. 2023), a comprehensive ranking system for evaluating embedding models. Following the recommended practices outlined by Ma (2023), the embedding

process incorporated the instruction "Cluster the text: " to optimize the resultant embeddings for downstream clustering tasks.

4.2. TOPIC MODELING AND RETRIEVAL AUGMENTED GENERATION

In generating topic labels, a two-stage prompt approach was employed, leveraging the capabilities of an advanced language model. The initial system prompt established the AI's role as an expert in topic labeling working on the specific theme at hand, instructing it to create accurate, concise labels based strictly on provided keywords. This was followed by a more detailed chat prompt, which outlined specific guidelines for the labeling process. The AI was directed to produce a short topic label, limited to 10 words as in Grootendorst (2022), based solely on the given keywords while disregarding any accompanying document samples. The prompt emphasized the importance of prioritizing initial keywords and reflecting only one main topic in the label. This structured methodology aimed to generate focused, relevant topic labels by utilizing the AI's natural language understanding and summarization abilities while maintaining a consistent approach across various subjects.

After topic generation, a retrieval augmented generation (RAG) protocol (Lewis et al. 2021) was employed to construct an AI-driven report providing concise topic descriptions and supporting references. Initially, each topic was compared against the title-abstract pairs extracted from the scientific corpus. Both topics and title-abstract pairs were embedded, and their semantic similarity was assessed using the dot product, identifying the 100 closest matches for each topic. Subsequently, deduplication was performed, removing chunks from the same reference and selecting only the one closest semantically to the topic, addressing potential redundancy where multiple title-abstract pairs originated from the same scientific article.

Further refinement involved prioritizing from the deduplicated 100 closest matches the top 20 most cited scientific texts based on Scopus citation counts, aligning with the principle of leveraging highly impactful research. Following established retrieval and re-ranking methodologies widely adopted in academic and industrial settings (Guo et al. 2022), the Voyage reranker was utilized to select from the 20 previously selected matches the three most relevant texts for each topic. Specifically, the reranker addressed the query: "Is this text related to the topic:

'{topic}'?" where '{topic}' represented the topic under consideration. The resulting references were then integrated into the report, providing context and support for each topic.

After identifying and ranking pertinent scientific literature, a system and chat prompt framework were implemented to generate summaries for each topic. The system prompt established the persona of a scientific expert tasked with extracting information exclusively from the provided abstracts. Complementing this, the chat prompt furnished detailed instructions for synthesizing a single-paragraph summary derived solely from the content of three selected abstract excerpts. This methodology aimed to produce a clear and focused summary of each topic grounded in the most relevant segments of the chosen scientific texts.

Following this summarization process, an automated report was generated. This report comprised a comprehensive list of topics, each accompanied by a concise summary and supporting references. The final report was then presented to the user in PDF format for convenient access and dissemination (see Appendix 6).

4.3. INTEGRATION INTO STRATEGIC ROADMAPPING

The final step aggregated these labeled topics, associated summaries, and supporting scientific references into a comprehensive AI-driven report delivered as a PDF. The experts then collaboratively used these topics to populate a strategic roadmap, systematically organized by time horizons and by key functional layers. During the roadmapping workshops, participants could adopt the auto-generated topics directly or derive new applications inspired by them. In this process, the experts used their domain knowledge to identify connections between related topics across different layers, creating a cohesive strategic framework that bridged current capabilities with future opportunities. The analysis yielded 55 distinct topics in the AgeTech case study.

The topics were described using RAG in a report-based structure. For example, the topic "Machine Learning-Based Fall Detection for Elderly" is accompanied by a summary that clarifies its meaning, detailing the research area by addressing the risks of falls, alongside the potential applications of machine learning in detecting falls among the elderly. Moreover, the summary is supported by references directly extracted from the database, enhancing both the reliability of the results and their utility for experts seeking to explore the topic further. By anchoring the generative model's output in the actual content of the references, the risk of hallucinations is minimized,

thereby allowing the model to concentrate on summarizing the relevant information, simplifying the task and enhancing the trustworthiness of the results.

As illustrated in Figure 20, the strategic roadmap incorporates 37 of the original 55 topics generated by our analysis, demonstrating the high utility rate of the AI-generated topics in roadmap construction. The topics are categorized into two groups: those directly extracted from the topic modeling analysis (shown in yellow) and those derived from the AI analysis but modified based on expert insights (shown in green). This categorization underscores the dual utility of the topics: they are valuable both in their original form for populating the roadmap and as catalysts for experts to develop new, strategically relevant topics, reflecting the synergy between AI and human expertise advocated by Lichtenthaler (2020).

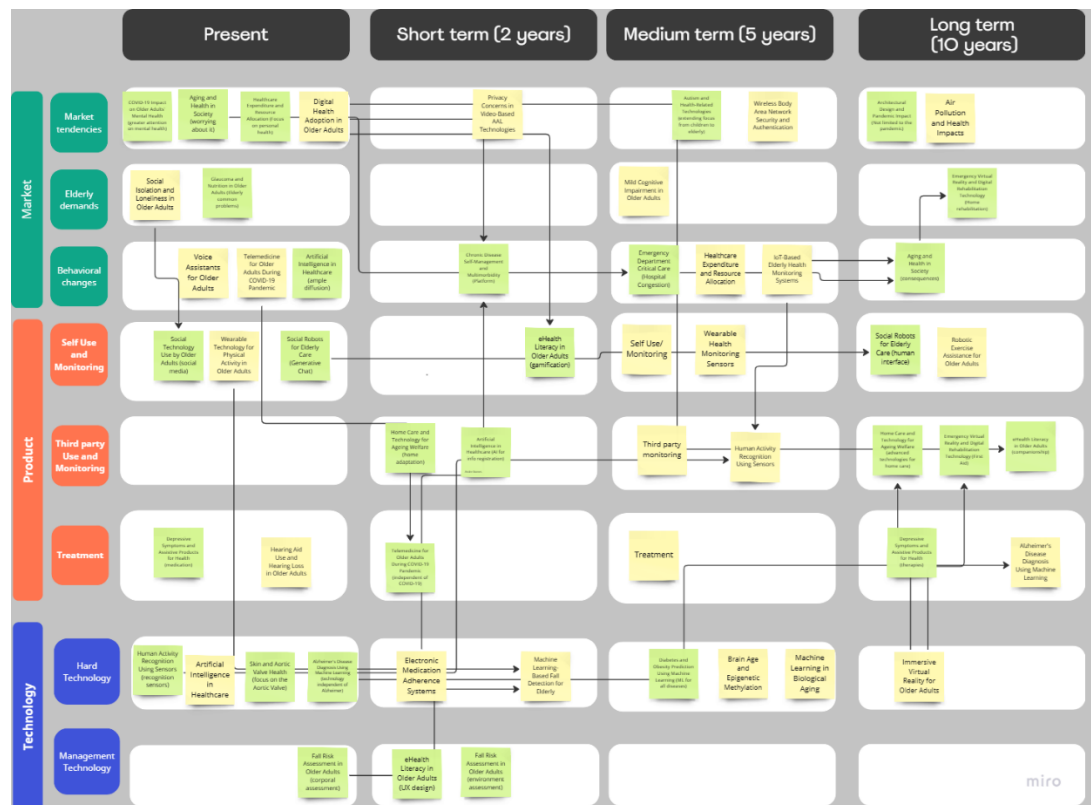


Fig. 20 Strategic roadmap for AgeTech

The roadmap's structure is organized into three main layers, each with its own subdivisions informed by the generated topics:

1. Market layer: market tendencies, elderly demands, and behavioral changes
2. Product layer: self-use and monitoring, third-party use and monitoring, and treatment
3. Technology layer: hard technology and management technology

This subdivision demonstrates the potential of automatically generated topics to create nuanced categories for strategic analysis.

The integration of AI-generated topics and expert insights in the roadmap highlights the importance of this hybrid approach in augmenting strategic decision-making. By leveraging large-scale data analysis, this method facilitates the creation of new topics, supports brainstorming, and enhances decision-making and strategic planning with foresight.

To illustrate the practical value of this approach, consider three exemplary topics:

1. "Social Robots for Elderly Care (Generative Chat)": This topic highlights the growing role of robotics and generative chats in addressing manpower shortages in elderly care (Macis, Perilli, and Gena 2022). Experts envisioned the development of simple, assistive robots within the next decade, categorizing this as a self-use and monitoring product.
2. "IoT-Based Elderly Health Monitoring Systems": This topic leverages advancements in physiologic sensory systems, stable wireless networks, and low-energy mechanics to enable remote health monitoring (Guizani and Guizani 2020). Experts identified this as a significant market trend related to behavioral changes, with a five-year implementation horizon.
3. "Machine Learning-Based Fall Detection for Elderly": This critical research area aims to improve safety and health outcomes for older adults by developing effective fall detection systems (Badgajar and Pillai 2020). Experts classified this as a hard technology with a short-term (two-year) focus.

In conclusion, the integration of topic modeling with Retrieval Augmented Generation (RAG) demonstrates value in corroborating existing strategic ideas and generating novel concepts for future implementation. The experts argued that the utility of topic modeling was enhanced by providing detailed descriptions of the topics in a report-based structure, based upon the most relevant references directly extracted from the database. As Choi et al. (2021) suggested, this method converts qualitative information from unstructured textual data into valuable quantitative

insights, offering a powerful tool for strategic decision-making in rapidly evolving technological landscapes.

4.4. EVALUATION PROCEDURES

The efficacy of the AI-based topic modeling approach for strategic development was evaluated through two distinct procedures, leveraging both semantic similarity analysis (Pennington, Socher, and Manning 2014) and expert domain knowledge. The first evaluation procedure focused on establishing the topic relevance within the context of each case study, with each of the domains for the cases being established together with the experts. In the case of AgeTech, the definition used to run the semantic similarity was "Health-related technology for the elderly."

The evaluation process was conducted after generating the topics. First, both the generated topics and the predefined subject definition were converted into vector representations using the Voyageai embedding model. This allowed for a mathematical assessment of their semantic relationships. Then, following Ma (2023), methodology, we calculated the dot product between these vector representations to quantify how closely each topic aligned with the subject definition. This approach provided an objective measure of topic relevance to the core subject matter.

Beyond that, expert feedback was extracted for each generated topic based on the work of Giorgi et al. (2024). The experts who provided this feedback were consultants experienced in facilitating roadmapping workshops across various industries, making them well-positioned to evaluate the strategic relevance and utility of the pre-populated topics generated through our AI-augmented approach. This expert evaluation encompassed three key dimensions: topic relevance, strategic utility, and reliability. Relevance, defined as the alignment of a topic with the core subject matter, was assessed based on: "Relevance (Select the topic's relevance based on the provided options, ensuring it aligns well with the subject matter)." Strategic utility, defined as the potential for a topic to inform strategic decision-making, was evaluated with: "Useful for strategy (Select if the topic is useful for your strategy purposes based on the provided options)." Finally, reliability, defined as the absence of hallucinations and the grounding of the topic in the underlying data source, was extracted with: "Reliability (Select the topic reliability based on the provided options,

ensuring that the topic is free from hallucinations and that the content is based on the researched data source)."

Each dimension was evaluated using a three-point scale ranging from 0 to 2, where 0 denoted "not relevant/not useful/not reliable," 1 indicated "partially relevant/partially useful/partially reliable," and 2 represented "relevant/useful/reliable." This evaluation methodology draws from research published by the Allen AI Institute (Giorgi et al. 2024), providing a structured approach to assess the quality of generated topics across multiple dimensions of practical importance.

Expert validation of the 55 identified topics indicated a high level of reliability, with 54 topics analyzed by the experts considered reliable and one partially reliable. This robust reliability underscores the effectiveness of integrating topic modeling with Retrieval Augmented Generation (RAG) for strategic development. By leveraging advancements in generative AI, this methodology ensures that the selected topics are grounded in a rigorous analytical framework and supported by references, addressing the challenges of information reliability highlighted by Lazaridou et al. (2022).

Building upon the identified relevance of topics within the growing AgeTech field, this research has garnered positive feedback for its significant contributions to the strategic planning processes of the company under study. This aligns with the growing recognition of the strategic implications of leveraging big data and AI in business contexts (Ardito 2019; von Krogh 2018). Expert evaluations have emphasized the role of topic modeling in establishing a data-driven foundation for identifying pertinent topics crucial to strategy development, supporting our approach of combining topic modeling with the latest developments in generative AI.

This methodology enhances the precision and relevance of strategic decisions by providing a systematic and evidence-based approach to the initial stages of strategic planning. This addresses the need for more robust strategic approaches in the rapidly evolving business landscape shaped by emerging technologies, as Agrawal et al. (2017) highlighted. Integrating data-driven insights into the company's strategic framework not only substantiates the decision-making process but, according to the experts, can showcase new topics that were not under their immediate radar. This demonstrates the potential of our approach to expand the scope of organizational knowledge integrated into strategic decision-making.

The ability to optimize the planning process and ensure that strategic directions are rooted in the latest research trends and industry developments aligns with recent work on using textual data sources for strategy formulation (Furman and Teodoridis 2020; Miric, Jia, and Huang 2022). By leveraging advanced NLP techniques and generative AI, our methodology provides a novel approach to bridging the gap between vast textual data and actionable strategic insights (Grimmer and Stewart 2013).

4.5. CROSS-INDUSTRY VALIDATION: RESULTS FROM DIVERSE CASE STUDIES

Considering the eight case studies of strategic development across healthcare, quantum computing, and manufacturing, we collected data using an evaluation procedure to calculate reliability, relevance, and alignment with strategy. 398 topics were generated from these eight cases, providing a larger sample for analysis compared to the previous results from the specific case related to AgeTech.

These results corroborate the perceived reliability in the AgeTech case, with experts considering 98.7% of the topics to be reliable, 0.5% to be somewhat reliable, and 0.7% to be not reliable. The experts attribute this high reliability to the explained methodology and, in particular, to the supporting references directly extracted from a database, reducing the possibility of hallucinations. This high reliability rate supports our claim that integrating generative AI with a Retrieval Augmented Generation (RAG) protocol provides a more efficient, scalable, and reliable approach to extracting strategic insights from rich textual data sources (Lewis et al. 2021).

When we consider the relevance of the topics to the subject at hand, 27% of the topics are deemed relevant, 11% are somewhat relevant, and 61% are not relevant. This indicates that while a significant percentage of the topics are considered relevant, the majority were not sufficiently relevant to the subject under research. Such results are expected in topic modeling, as a large sample of documents under analysis will inevitably cover a diverse range of topics, with only some being pertinent to the subject under study. Previous researchers have pointed out that topic modeling, especially BERTopic, generates many outliers, which is a current limitation of the algorithm (Egger and Yu 2022).

Case	Not strategically relevant	Somewhat strategically relevant	Strategically relevant
1	75%	8%	18%
2	79%	9%	13%
3	72%	18%	10%
4	33%	8%	59%
5	78%	10%	12%
6	31%	8%	61%
7	83%	8%	10%
8	79%	12%	9%

Table 8 Strategic relevancy of the results in the 8 case studies

Table 8 presents data on the strategic relevance of topics across the eight different cases, revealing significant variations in their utility for strategic purposes. This variation aligns with our earlier discussion on the importance of context in strategic decision-making. For instance, Cases 4 and 6 show a notably high percentage of strategically relevant topics (59% and 61% respectively), indicating that the AI-generated insights were particularly valuable in these contexts. Specifically, Case 6 achieved high strategic relevance because, according to the expert consultant, the data accurately represented the subject area and the organization was seeking a general landscape understanding of the market. The current model demonstrates particular strength in providing such comprehensive market overviews.

In contrast, Cases 7 and 8 demonstrate a much lower percentage of strategically relevant topics (10% and 9% respectively), suggesting that the generated insights were less directly applicable to the strategic needs of these cases. Case 8's low relevance can be attributed to its very specific demands that were difficult to capture from title and abstract data alone, combined with a need for identifying weak signals for highly specialized requirements. These are areas where the current methodology faces limitations. The variation in strategic relevance across different cases highlights the critical role of human expertise in interpreting and applying these AI-generated insights within the specific strategic context of each organization (Lichtenthaler 2020).

The variation in strategic relevance across cases can be further explained by examining the inherent nature of topic modeling methodologies. Topic modeling algorithms like BERTopic extract all topics present in the text corpus, regardless of their direct relevance to the primary subject under investigation. Since the initial text collection was performed using keyword matching, documents often contain peripheral discussions that, while matching the search terms, address tangentially related or entirely different matters. Furthermore, it is important to note that for evaluation purposes, topics were intentionally not pre-filtered using semantic similarity measures, ensuring a comprehensive assessment of all possible topics generated by the algorithm. This methodological choice was deliberate, as a subsequent evaluation using semantic similarity was conducted separately, which can be used in future implementations to filter topics before presenting them to strategists. Such filtering mechanisms would increase the proportion of strategically relevant topics presented to decision-makers, thereby enhancing the practical utility of the framework while maintaining the underlying analytical rigor that produced the high reliability scores (exceeding 98%) in topic identification

Additionally, we should consider the percentage of topics deemed useful for the experts' strategic purposes. Of these, 22% are considered strategically relevant, 10% somewhat strategically relevant, and 68% not strategically relevant. This data reflects a decrease in the number of topics useful for strategic purposes compared to those relevant to the subject. This is expected, as each organization from which the experts are making decisions has different strategic perspectives, making some topics useful for one type of organization but not for another. The variation in strategic relevance across different organizations underscores the importance of our approach in providing a flexible framework for extracting strategic insights.

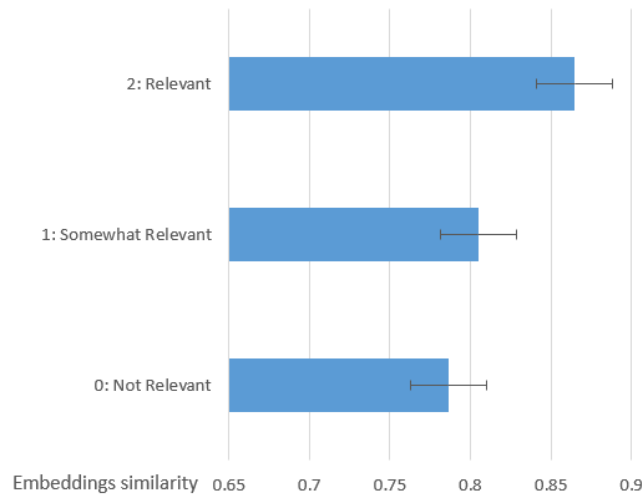


Fig. 21 Embedding similarity related to relevance, with standard error bars.

Finally, the results have an average similarity score of 0.864, somewhat relevant results have a similarity score of 0.804, and not relevant results have a similarity score of 0.786 (see Figure 21). These scores demonstrate that the results deemed more relevant by experts were also judged to be more similar to the subject under analysis by the embeddings' similarity. Therefore, the language models' quantitative outputs further corroborate the extracted topics' relevance.

The roadmapping sessions brought together domain specialists who worked on translating AI-generated insights into actionable strategic plans. These visual roadmaps served as valuable tools for strategic discussions, allowing experts to identify connections between market needs and technological capabilities. The process demonstrated how AI-generated topics could effectively augment human expertise and creativity in strategic planning, providing both verification of existing strategic directions and introducing novel perspectives that might otherwise have been overlooked.

4.6. AI-AUGMENTED ROADMAPPING SECOND APPLICATION DISCUSSION

The second application enhanced the initial methodology by incorporating retrieval-augmented generation (RAG) capabilities to produce topic-based reports with supporting scientific references. This refinement enabled the generation of comprehensive topic summaries directly grounded in source documents, significantly reducing the risk of hallucinations while

enhancing reliability as noted by Lazaridou et al. (2022). The implementation processed domain-specific literature through neural topic modeling (Grootendorst 2022) and created a verification mechanism that ensured all content was explicitly connected to authoritative sources.

When validated across eight diverse industry contexts, the approach was considered reliable, with 98.7% of topics deemed reliable by domain experts. This cross-industry validation confirmed the method's versatility beyond its original application context, establishing its broader value as an approach to AI-augmented strategic roadmapping.

While highly effective at automating insight extraction, the second application was designed to complement rather than replace human expertise, consistent with findings from Agrawal et al. (2017). Domain specialists remained essential for interpreting results, contextualizing insights within organizational priorities, and making final strategic decisions. This balanced approach to human-AI collaboration addressed the need for more sophisticated approaches to roadmapping in the AI-driven landscape. The artifact developed through this research is readily accessible on GitHub (<https://github.com/DataGomes/ReportRAG>).

5. INSIGHTS FOR FUTURE RESEARCHERS AND PRACTITIONERS

This chapter synthesizes the key learnings from our research into guidelines for researchers and practitioners interested in implementing AI-augmented approaches to strategic roadmapping. The knowledge derived from the systematic literature review and the empirical applications yield several important insights that can guide future efforts in this domain.

5.1. DESIGN PRINCIPLES FOR AI-AUGMENTED ROADMAPPING

5.1.1. BALANCE AUTOMATION WITH EXPERT JUDGMENT

The first principle that is validated by our research is the importance of maintaining a balanced relationship between AI-driven automation and expert judgment. While our implementation demonstrated the substantial value of AI in extracting and organizing strategic insights from large textual corpora, the expert-driven interpretation and contextualization of these insights proved equally critical. This finding aligns with previous research suggesting that AI's most beneficial impact is in augmenting managers' capacities rather than replacing them (Agrawal et al. 2017).

Insight 1: *AI-augmented roadmapping systems should be designed as decision support tools that enhance rather than replace expert judgment, clearly delineating automated and human-driven components in the process.*

This insight substantiates the complementary relationship between AI capabilities and human expertise in strategic planning contexts, supporting Lichtenthaler's (2020) argument that combining artificial and human intelligence creates significant strategic advantages.

5.1.2. GROUND AI-GENERATED INSIGHTS IN RELIABLE SOURCES

A critical challenge in integrating generative AI into strategic planning processes is ensuring the reliability of the generated insights. Our implementation of Retrieval-Augmented Generation (RAG) validated the effectiveness of anchoring AI-generated content directly to source materials, with experts deeming 98.7% of topics reliable across eight case studies.

Insight 2: *AI-augmented roadmapping implementations should employ retrieval-augmented generation techniques that explicitly connect strategic insights to their evidentiary basis in source documents.*

This approach addresses concerns about hallucinations and factual inaccuracies that have been raised regarding generative AI systems (Lazaridou et al. 2022). By designing systems that maintain clear links between insights and sources, organizations can leverage AI's pattern recognition capabilities while maintaining the verifiability that is essential for strategic decision-making.

5.1.3. LEVERAGE NEURAL TOPIC MODELING FOR DISCOVERY

Our research demonstrated that neural topic modeling approaches like BERTopic (Grootendorst 2022) can overcome the limitations of traditional topic models by incorporating word embeddings and capturing semantic relationships. This capability enabled the discovery of non-obvious connections between strategic topics that might be overlooked in expert-only approaches.

Insight 3: *Strategic roadmapping can benefit from neural topic modeling techniques that capture semantic relationships between concepts, allowing for the discovery of non-obvious connections between market needs, products, and technologies across time horizons.*

The ability to discover unexpected connections aligns with recent work on using intelligent systems to create comprehensive strategies for search and innovation discovery (Bahceci et al. 2023). By implementing neural topic modeling as part of the roadmapping process, organizations can reduce cognitive biases that might otherwise limit the scope of strategic exploration.

5.2. IMPLEMENTATION STRATEGIES FOR PRACTITIONERS

5.2.1. ADOPT AN ITERATIVE APPROACH TO IMPLEMENTATION

The evolution of our artifact from the first application to the second demonstrated the value of an iterative approach to implementing AI-augmented roadmapping. Initial implementations can focus on basic topic extraction and visualization, with subsequent refinements incorporating more sophisticated techniques like retrieval-augmented generation.

Insight 4: *Organizations should adopt a phased, incremental approach to AI-augmented roadmapping that builds competency while progressively enhancing capabilities.*

Our thesis substantiates this insight through the documented progression between our first and second implementations. The comparative analysis in our research provides evidence of how incremental refinement improved outcomes in an actual organizational context. This empirical work extends Hirose et al.'s (2020) roadmapping maturity model by specifically demonstrating how AI-augmented approaches benefit from staged implementation, allowing organizations to build acceptance and expertise while managing risks.

5.2.2. CUSTOMIZE DATA SOURCES FOR STRATEGIC CONTEXT

Our research demonstrated the importance of selecting appropriate data sources for AI-augmented roadmapping. Each of our eight case studies utilized a tailored corpus of scientific literature specifically relevant to the domain under analysis, based upon keywords chosen by experts. For example, in the AgeTech case, we used specialized healthcare and gerontechnology articles, while other cases required targeted literature from quantum computing, manufacturing, and other domains.

Insight 5: *AI-augmented roadmapping implementations should be tailored to incorporate the specific mix of data most relevant to an organization's strategic context, particularly for the pre-population phase where domain-specific sources are analyzed.*

This insight is supported by our cross-industry validation, where we customized search strategies for each case to ensure domain relevance. The effectiveness of AI-augmented roadmapping depends significantly on selecting input data that aligns with the specific strategic objectives and industry context of the organization.

5.2.3. ENSURE TRANSPARENCY AND EXPLAINABILITY

Integrating AI techniques into strategic roadmapping raises important questions about transparency and explainability. Our implementation prioritized mechanisms for understanding how AI-generated insights are derived, particularly through the use of retrieval-augmented generation that explicitly links insights to source materials.

Insight 6: *AI-augmented roadmapping implementations should incorporate explainability mechanisms that allow stakeholders to trace the origins of topics proposed for each layer, understand their temporal positioning, and examine the criteria that shaped the pre-population analysis.*

This insight recognizes that strategic decision-makers need to trust the outputs of AI systems before acting on them. By implementing topic modeling algorithms in an open way, that reveal their parameters, providing clear linkages between extracted topics and source documents, and demonstrating the evidence chain from literature to roadmap elements, organizations can establish confidence in the AI-augmented approach while maintaining the necessary rigor for strategic planning.

6. CONCLUSION

Strategic planning in the digital era faces significant challenges as organizations navigate complex technological landscapes while contending with extensive information volumes. This thesis addressed the problem of incorporating advanced AI technologies, specifically neural topic modeling and retrieval-augmented generation, into strategic roadmapping processes to enhance reliability and augment human capabilities in strategic knowledge extraction and interpretation.

This research specifically focused on enhancing the pre-population phase of the strategic roadmapping process. This phase, which precedes the collaborative workshops, was identified as the area where AI augmentation could provide the most significant value by systematically extracting and organizing strategic insights from vast textual databases. By concentrating on pre-population, the research addresses a critical bottleneck in roadmapping where human experts often struggle to comprehensively analyze the breadth of available information.

Therefore, in this study, we introduce a novel approach combining topic modeling with generative AI and RAG to extract strategic insights from large-scale textual databases to enhance strategic planning foresight capabilities. Our systematic literature review revealed a significant growth in the intersection of artificial intelligence, business strategy, and technology roadmapping since 2015. This growth trend reflects the increasing importance of AI-driven methodologies in strategic planning processes, particularly in technology roadmapping.

The bibliometric analysis and historical analysis demonstrated that AI has been increasingly applied in strategy and technology roadmaps, with deep learning and natural language processing techniques gaining prominence recently. Specifically, the LDA and BERTopic analysis revealed several themes in the scientific discourse on AI, business strategy, and technology roadmapping. The most notable subject matter revolves around the increasing use of data analytics and AI-driven methods in strategic planning and decision-making processes.

Our research methodology progressed through two distinct applications of AI-augmented roadmapping. The first application in the AgeTech domain was an initial proof-of-concept, using BERTopic for clustering and topic labeling to augment traditional roadmapping processes. This implementation demonstrated the feasibility of using neural topic modeling to extract strategic insights from scientific literature, with 44% of topics in the final roadmap derived from our quantitative analysis. Building on this foundation, our second application enhanced the methodology with retrieval-augmented generation (RAG) capabilities, producing topic-based reports with supporting scientific references. This refined approach was validated across eight diverse industry contexts, demonstrating its broad applicability beyond the AgeTech domain.

The validation across eight diverse case studies demonstrates the approach's reliability, with 98.7% of generated topics deemed reliable by domain experts. As strategies in this area continuously evolve, these tools can supply invaluable insights while maintaining reliability through careful grounding in source documents.

6.1. THEORETICAL CONTRIBUTIONS

The primary contribution of this thesis lies in its ability to provide a robust framework for reliably extracting and synthesizing strategic insights from large data sources, thereby augmenting traditional foresight methods and enhancing the digital roadmapping process. As highlighted by Kapoor & Wilde (2023), foresight is fundamental to strategic planning, encompassing various methods to anticipate and shape the future. Our approach significantly enhances this capability by efficiently processing and analyzing vast textual data to identify emerging trends.

Similarly, in digital roadmapping, our research addresses the need for more sophisticated, data-driven approaches as noted by Oliveira et al. (2023). By automatically extracting relevant

topics and trends from textual databases, our approach provides a solid, evidence-based foundation for constructing strategic roadmaps, enhancing their accuracy and forward-looking nature.

Traditional approaches to strategic analysis and roadmapping often struggle with the sheer volume of available information (Hannigan et al. 2019). Moreover, while powerful, recent advancements in generative AI have raised concerns about the reliability and factual accuracy of their outputs (Lazaridou et al. 2022). Our method addresses these issues by grounding AI-generated insights directly in the textual corpus, significantly reducing the risk of hallucinations or inaccuracies. This is particularly crucial in foresight and roadmapping, where the reliability of future-oriented insights can significantly impact strategic decision-making.

The reliability of our approach is demonstrated through several key aspects:

1. Data-driven topic identification: Our method utilizes BERTopic (Grootendorst 2022) to ensure that identified topics are based on actual patterns in the texts rather than preconceived notions or limited human analysis.
2. Contextual relevance: Embedding models (Ma 2023) allows for a nuanced understanding of semantic relationships within the text, ensuring that extracted topics are contextually relevant.
3. Fact-based summarization: Our implementation of RAG (Lewis et al. 2021) ensures that topic summaries are directly tied to specific parts of the texts, providing a clear trail of evidence for each insight.
4. Expert validation: Our evaluation's high reliability scores (98.7% of topics considered reliable by experts across eight case studies) demonstrate the trustworthiness of the generated insights.
5. Transparent methodology: By providing a detailed, step-by-step explanation of our process, we allow for critical examination of the method.

This reliable approach to extracting strategic insights addresses a crucial need in both academia and industry. As Keding (2020) noted, there is a significant gap in understanding the strategic integration of AI in business contexts. Our method bridges the vast amount of available textual data and actionable strategic insights, offering a reliable tool for decision-makers to navigate complex technological landscapes.

Furthermore, our approach aligns with recent calls for more robust and data-driven strategic decision-making processes (Agrawal et al. 2017; Helfat et al. 2023). By providing a method to synthesize insights from large-scale databases, we enable organizations to make more informed and evidence-based strategic decisions.

The application of our method demonstrates its practical utility in identifying emerging trends and opportunities. This aligns with the need for comprehensive search and innovation discovery strategies, as Bahceci et al. (2023) highlighted. The integration of topic modeling with digital roadmapping showcases how our method can enhance existing strategic planning tools. This addresses the need for more sophisticated approaches to roadmapping in the AI-driven landscape (Oliveira et al., 2022; Kerr and Phaal, 2022; Oliveira et al., 2023).

6.2. PRACTICAL CONTRIBUTIONS

This research provides actionable contributions for practitioners seeking to enhance their strategic roadmapping through AI integration. First, we developed an implementable framework that organizations can directly apply to augment their roadmapping practices, available as an open-source tool on GitHub (<https://github.com/DataGomes/ReportRAG>). This artifact enables organizations to process large volumes of scientific literature and extract strategically relevant topics without requiring extensive expertise in artificial intelligence or natural language processing.

Second, we demonstrated a phased implementation approach that organizations can follow to gradually integrate AI into their existing roadmapping processes. The initial phase, as shown in our AgeTech case study, provides an accessible entry point using neural topic modeling for topic identification and clustering. This allows organizations to quickly enhance their roadmapping workshops while maintaining the collaborative aspects that make traditional roadmapping effective.

Third, our enhanced methodology incorporating retrieval-augmented generation addresses a critical practical challenge: ensuring the reliability and traceability of AI-generated insights in strategic contexts. By explicitly connecting strategic topics to scientific references in a report-like structure, the approach provides decision-makers with verifiable evidence for strategic decisions, addressing concerns about AI trustworthiness that have limited previous applications (Bommasani et al. 2022; Kenton et al. 2021).

Fourth, our validation across eight diverse industry contexts through live projects demonstrates the methodology's trustworthiness. The high reliability ratings (98.7% of topics deemed reliable by domain experts) provide empirical evidence of the approach's value in real-world strategic planning scenarios, enabling confident application across different organizational contexts.

Finally, the report-driven approach transforms abstract topics into comprehensive, evidence-based documents that strategic planners can directly incorporate into their decision-making processes. By augmenting human expertise with AI-powered knowledge extraction, the approach enables more comprehensive strategic foresight while preserving the visual and collaborative strengths that make traditional roadmapping valuable (Kerr and Phaal 2022).

6.3. LIMITATIONS

Despite its contributions, the approach has limitations. First, the results of the method depends on the quality and comprehensiveness of the input data. While the research utilized the Scopus database, which offers broad interdisciplinary scope, inherent biases or gaps in published literature could influence the extracted insights, potentially amplifying existing biases or overlooking emerging trends not yet represented in scholarly articles.

Second, while the approach mitigates the risk of hallucinations through retrieval-augmented generation, the potential for misinterpretation or inaccurate synthesis of information remains. The complexity of strategic foresight requires nuanced understanding and contextual knowledge that may challenge AI systems to capture, potentially leading to simplified recommendations.

Third, the current focus on textual data analysis may not capture the full spectrum of information necessary for comprehensive strategic planning. The data sources were limited to the titles and abstracts of scientific texts, not contemplating the whole text. Strategic foresight benefits from diverse data sources, including quantitative data, expert opinions, and real-time market signals, which the method does not currently incorporate.

Fourth, a limitation of our approach is the inherent challenge of using historical data to predict future strategic developments. Strategic planning, by its nature, seeks to anticipate future market conditions, technological capabilities, and business opportunities that may differ substantially from past patterns. Our methodology analyzes frequency of topics in historical

scientific publications to populate roadmaps, but this assumes that past research interests and publication patterns are indicative of future strategic relevance. Additionally, our approach does not incorporate growth rates or acceleration patterns that might better indicate emerging opportunities. In strategic planning contexts where discontinuous innovation and market disruption are common, relying on historical data frequency may miss weak signals of transformative changes that have yet to manifest in publication volumes.

Finally, the strategic utility of the extracted topics varied across different organizational contexts, highlighting the challenge of developing a universally applicable method for strategic foresight. The relevance and actionability of insights depend on organizational context and may require substantial human interpretation and adaptation.

6.4. FUTURE RESEARCH DIRECTIONS

This research opens several promising avenues for future investigation. First, integrating the entire sources of scientific texts and a more diverse range of sources. Beyond that, multi-modal data sources beyond textual information could enhance the comprehensiveness of strategic insights. Exploring frameworks for incorporating quantitative metrics, images, and structured databases alongside textual analysis would provide more holistic support for strategic decision-making.

Second, developing real-time AI-augmented roadmapping capabilities could enable continuous strategic adaptation rather than periodic roadmapping exercises. This would require investigating methodologies for processing streaming data and updating strategic insights in response to changing environments.

Third, cross-lingual and cross-cultural capabilities represent an important area for future development, enabling global organizations to leverage diverse perspectives in their strategic planning. This would require adapting the approach to handle multiple languages and cultural contexts while maintaining reliability and relevance.

Fourth, investigating methods for long-term impact assessment of AI-augmented strategic decisions would provide valuable feedback for refining these approaches. This could include exploring domains with precise outcome measurements, such as investment strategy where returns are quantifiable, or medicine where clinical outcomes provide clear metrics. Longitudinal studies

in these fields would enable rigorous validation of the predictive value of AI-generated strategic insights.

Fifth, addressing the limitation of historical frequency-based analysis, future research should develop more sophisticated approaches for strategic foresight. This includes incorporating growth rate analysis and weak signal detection, as well as exploring the use of large language models as evaluators ("LLM-as-a-judge") to provide scalable assessment of strategic relevance. Additionally, extending LLM support beyond pre-population to facilitate real-time collaboration during workshops could transform roadmapping into a more dynamic process. The increasing availability of open-source models like LLaMA and DeepSeek also presents opportunities for more accessible implementations, particularly for organizations with specific security or customization requirements.

The open-source nature of the code used in this research facilitates future developments, enabling collaborative advancement of AI-augmented foresight techniques. The integration of AI-driven methodology with human expertise promises to transform how organizations approach long-term planning. By harnessing AI's capacity to process vast information volumes while maintaining human oversight and strategic intuition, organizations can navigate complex and evolving landscapes with enhanced confidence and foresight.

7. REFERENCES

- Abai, Nur Hani Zulkifli; Yahaya, Jamaiah; Deraman, Aziz; Hamdan, Abdul Razak; Mansor, Zulkefli; Jusoh, Yusmadi Yah. 2019. "Integrating Business Intelligence and Analytics in Managing Public Sector Performance: An Empirical Study." *International Journal on Advanced Science, Engineering and Information Technology* 9(1):172–80. doi: 10.18517/ijaseit.9.1.6694.
- Aggarwal, Charu, Alexander Hinneburg, and Daniel Keim. 2002. "On the Surprising Behavior of Distance Metric in High-Dimensional Space." *First Publ. in: Database Theory, ICDT 200, 8th International Conference, London, UK, January 4 - 6, 2001 / Jan Van Den Bussche ... (Eds.). Berlin: Springer, 2001, Pp. 420-434 (=Lecture Notes in Computer Science ; 1973).*
- Agrawal, Ajay, Joshua S. ;. Stern Gans Scott, and Avi Goldfarb. 2017. "What to Expect From Artificial Intelligence." *MIT Sloan Management Review*. Retrieved June 15, 2023 (<https://sloanreview.mit.edu/article/what-to-expect-from-artificial-intelligence/>).
- Akoka, Jacky, Isabelle Comyn-Wattiau, Nicolas Prat, and Veda C. Storey. 2023. "Knowledge Contributions in Design Science Research: Paths of Knowledge Types." *Decision Support Systems* 166:113898. doi: 10.1016/j.dss.2022.113898.
- de Alcantara, Douglas Pedro; Martens, Mauro Luiz. 2019. "Technology Roadmapping (TRM): A Systematic Review of the Literature Focusing on Models." *Technological Forecasting and Social Change* 138(NA):127–38. doi: 10.1016/j.techfore.2018.08.014.
- Ardito, Lorenzo; Scuotto, Veronica; Del Giudice, Manlio; Petruzzelli, Antonio Messeni. 2019. "A Bibliometric Analysis of Research on Big Data Analytics for Business and Management." *Management Decision* 57(8):1993–2009. doi: 10.1108/md-07-2018-0754.
- Azzam, Mark, and Rasmus Beckmann. 2022. "How AI Helps to Increase Organizations' Capacity to Manage Complexity – A Research Perspective and Solution Approach Bridging Different Disciplines." *IEEE Transactions on Engineering Management* 1–14. doi: 10.1109/TEM.2022.3179107.
- Badgujar, Sejal, and Anju S. Pillai. 2020. "Fall Detection for Elderly People Using Machine Learning." Pp. 1–4 in *2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*. Kharagpur, India: IEEE.
- Bahceci, Erkin, Riitta Katila, and Risto Miikkulainen. 2023. "Evolving Strategies for Competitive Multi-Agent Search."
- Baker, Lynne Rudder. 2004. "The Ontology of Artifacts." *Philosophical Explorations* 7(2):99–111. doi: 10.1080/13869790410001694462.
- Bergman, Erik, Anna Maria Gerdina Pasmooij, Peter G. M. Mol, and Gabriel Westman. 2023. "A Full-Document Analysis of the Semantic Relation between European Public Assessment

- Reports and EMA Guidelines Using a BERT Language Model” edited by D. Gotham. *PLOS ONE* 18(12):e0294560. doi: 10.1371/journal.pone.0294560.
- Bildosola, Iñaki; Río-Belver, Rosa; Garechana, Gaizka; Cilleruelo, Ernesto. 2017. “TeknoRoadmap, an Approach for Depicting Emerging Technologies.” *Technological Forecasting and Social Change* 117(NA):25–37. doi: 10.1016/j.techfore.2017.01.015.
- Blei, David M., Ng, and Jordan. 2003. “Latent Dirichlet Allocation.”
- Bommasani, Rishi, Drew A. Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S. Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, Erik Brynjolfsson, Shyamal Buch, Dallas Card, Rodrigo Castellon, Niladri Chatterji, Annie Chen, Kathleen Creel, Jared Quincy Davis, Dora Demszky, Chris Donahue, Moussa Doumbouya, Esin Durmus, Stefano Ermon, John Etchemendy, Kawin Ethayarajh, Li Fei-Fei, Chelsea Finn, Trevor Gale, Lauren Gillespie, Karan Goel, Noah Goodman, Shelby Grossman, Neel Guha, Tatsunori Hashimoto, Peter Henderson, John Hewitt, Daniel E. Ho, Jenny Hong, Kyle Hsu, Jing Huang, Thomas Icard, Saahil Jain, Dan Jurafsky, Pratyusha Kalluri, Siddharth Karamcheti, Geoff Keeling, Fereshte Khani, Omar Khattab, Pang Wei Koh, Mark Krass, Ranjay Krishna, Rohith Kuditipudi, Ananya Kumar, Faisal Ladhak, Mina Lee, Tony Lee, Jure Leskovec, Isabelle Levent, Xiang Lisa Li, Xuechen Li, Tengyu Ma, Ali Malik, Christopher D. Manning, Suvir Mirchandani, Eric Mitchell, Zanele Munyikwa, Suraj Nair, Avanika Narayan, Deepak Narayanan, Ben Newman, Allen Nie, Juan Carlos Niebles, Hamed Nilforoshan, Julian Nyarko, Giray Ogut, Laurel Orr, Isabel Papadimitriou, Joon Sung Park, Chris Piech, Eva Portelance, Christopher Potts, Aditi Raghunathan, Rob Reich, Hongyu Ren, Frieda Rong, Yusuf Roohani, Camilo Ruiz, Jack Ryan, Christopher Ré, Dorsa Sadigh, Shiori Sagawa, Keshav Santhanam, Andy Shih, Krishnan Srinivasan, Alex Tamkin, Rohan Taori, Armin W. Thomas, Florian Tramèr, Rose E. Wang, William Wang, Bohan Wu, Jiajun Wu, Yuhuai Wu, Sang Michael Xie, Michihiro Yasunaga, Jiaxuan You, Matei Zaharia, Michael Zhang, Tianyi Zhang, Xikun Zhang, Yuhui Zhang, Lucia Zheng, Kaitlyn Zhou, and Percy Liang. 2022. “On the Opportunities and Risks of Foundation Models.”
- Bryant, Benjamin P., and Robert J. Lempert. 2010. “Thinking inside the Box: A Participatory, Computer-Assisted Approach to Scenario Discovery.” *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE* 77(1):34–49.
- Callon, Michel; Courtial, Jean-Pierre; Turner, William A. ;. Bauin, Serge. 1983. “From Translations to Problematic Networks: An Introduction to Co-Word Analysis.” *Social Science Information* 22(2):191–235. doi: 10.1177/053901883022002003.
- Cao, Guangming; Duan, Yanqing; Li, Gendao. 2015. “Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis.” *IEEE Transactions on Engineering Management* 62(3):384–95. doi: 10.1109/tem.2015.2441875.
- Castro, Camila Gonçalves, Adriana Hofmann Trevisan, Daniela C. A. Pigosso, and Janaina Mascarenhas. 2022. “The Rebound Effect of Circular Economy: Definitions, Mechanisms

- and a Research Agenda.” *Journal of Cleaner Production* 345:131136. doi: 10.1016/j.jclepro.2022.131136.
- Cheng, Huaqing, Shengquan Liu, Weiwei Sun, and Qi Sun. 2023. “A Neural Topic Modeling Study Integrating SBERT and Data Augmentation.” *Applied Sciences* 13(7):4595. doi: 10.3390/app13074595.
- Chiang, Wei-Lin, Lianmin Zheng, Ying Sheng, Anastasios Nikolas Angelopoulos, Tianle Li, Dacheng Li, Hao Zhang, Banghua Zhu, Michael Jordan, Joseph E. Gonzalez, and Ion Stoica. 2024. “Chatbot Arena: An Open Platform for Evaluating LLMs by Human Preference.”
- Chien, T. W., C. Lin, B. Tan, and W. Chuan Lee. 1999. “A Neural Networks-Based Approach for Strategic Planning.” *Information and Management* 35(6):357–64. doi: 10.1016/S0378-7206(98)00100-1.
- Choi, Jaeho, Anoop Menon, and Haris Tabakovic. 2021. “Using Machine Learning to Revisit the Diversification–Performance Relationship.” *Strategic Management Journal* 42(9):1632–61. doi: 10.1002/smj.3317.
- Choi, Sungchul, Hongbin Kim, Janghyeok Yoon, Kwangsoo Kim, and Jae Yeol Lee. 2013. “An SAO-Based Text-Mining Approach for Technology Roadmapping Using Patent Information.” *R & D MANAGEMENT* 43(1):52–74.
- Chunlei Ye and Lu Feng. 2013. “Future-Oriented Technology Analysis of Technology Roadmap Based on Text Mining.” Pp. 1126–30 in *2013 10th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*. Shenyang, China: IEEE.
- Dalmau-Espert, J. L. ; Llorens-Largo, Faraón; Compañ-Rosique, Patricia; Satorre-Cuerda, Rosana; Molina-Carmona, Rafael. 2016. “Leveraging Information For High Level-of-Abstraction Organizational Processes.” *International Journal of Design & Nature and Ecodynamics* 11(3):416–27. doi: 10.2495/dne-v11-n3-416-427.
- Davenport, Thomas H. ; Kirby, Julia. 2016. “Just How Smart Are Smart Machines.” *MIT Sloan Management Review* 57(3):21–25.
- Davis, Christopher W. H. ; Jetter, Antonie J. ; Giabbanelli, Philippe J. 2022. “Automatically Generating Scenarios from a Text Corpus: A Case Study on Electric Vehicles.” *Sustainability* 14(13):7938–7938. doi: 10.3390/su14137938.
- Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. “BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding.” doi: 10.48550/ARXIV.1810.04805.

- Di Ciccio, Claudio; Marrella, Andrea; Russo, Alessandro. 2014. "Knowledge-Intensive Processes: Characteristics, Requirements and Analysis of Contemporary Approaches." *Journal on Data Semantics* 4(1):29–57. doi: 10.1007/s13740-014-0038-4.
- Donthu, Naveen, Dwayne D. Gremler, Satish Kumar, and Debidutta Pattnaik. 2022. "Mapping of *Journal of Service Research* Themes: A 22-Year Review." *Journal of Service Research* 25(2):187–93. doi: 10.1177/1094670520977672.
- Donthu, Naveen, Satish Kumar, Debmalya Mukherjee, Nitesh Pandey, and Weng Marc Lim. 2021. "How to Conduct a Bibliometric Analysis: An Overview and Guidelines." *Journal of Business Research* 133:285–96. doi: 10.1016/j.jbusres.2021.04.070.
- Egger, Roman, and Joanne Yu. 2022. "A Topic Modeling Comparison Between LDA, NMF, Top2Vec, and BERTopic to Demystify Twitter Posts." *Frontiers in Sociology* 7:886498. doi: 10.3389/fsoc.2022.886498.
- Eppler, Martin J., and Ken W. Platts. 2009. "Visual Strategizing." *Long Range Planning* 42(1):42–74. doi: 10.1016/j.lrp.2008.11.005.
- Evans, James A., and Pedro Aceves. 2016. "Machine Translation: Mining Text for Social Theory." *Annual Review of Sociology* 42(1):21–50. doi: 10.1146/annurev-soc-081715-074206.
- Feng, Lijie; Niu, Yuxiang; Wang, Jinfeng. 2020. "Development of Morphology Analysis-Based Technology Roadmap Considering Layer Expansion Paths: Application of TRIZ and Text Mining." *Applied Sciences* 10(23):8498-NA. doi: 10.3390/app10238498.
- Feng, Lijie; Zhao, Weiyu; Wang, Jinfeng; Lin, Kuo-Yi; Guo, Yanan; Zhang, Luyao. 2022. "Data-Driven Technology Roadmaps to Identify Potential Technology Opportunities for Hyperuricemia Drugs." *Pharmaceuticals (Basel, Switzerland)* 15(11):1357–1357. doi: 10.3390/ph15111357.
- Ferras-Hernandez, Xavier. 2018. "The Future of Management in a World of Electronic Brains." *JOURNAL OF MANAGEMENT INQUIRY* 27(2):260–63.
- Févotte, Cédric, and Jérôme Idier. 2011. "Algorithms for Nonnegative Matrix Factorization with the β -Divergence." *Neural Computation* 23(9):2421–56. doi: 10.1162/NECO_a_00168.
- Furman, Jeffrey L., and Florenta Teodoridis. 2020. "Automation, Research Technology, and Researchers' Trajectories: Evidence from Computer Science and Electrical Engineering." *Organization Science* 31(2):330–54. doi: 10.1287/orsc.2019.1308.
- Gentzkow, Matthew, Bryan Kelly, and Matt Taddy. 2019. "Text as Data." *Journal of Economic Literature* 57(3):535–74. doi: 10.1257/jel.20181020.

- Geum, Youngjung; Lee, Hakyeon; Park, Yongtae. 2012. "How to Use the Big Data to the Technology Planning: A Data-Driven Technology Roadmapping Using ARM." *2012 IEEE International Conference on Industrial Engineering and Engineering Management NA(NA)*:661–65. doi: 10.1109/ieem.2012.6837822.
- Geum, Youngjung; Lee, HyeonJeong; Lee, Youngjo; Park, Yongtae. 2015. "Development of Data-Driven Technology Roadmap Considering Dependency: : An ARM-Based Technology Roadmapping." *Technological Forecasting and Social Change* 91(1):264–79. doi: 10.1016/j.techfore.2014.03.003.
- Giorgi, John, Amanpreet Singh, Doug Downey, Sergey Feldman, and Lucy Lu Wang. 2024. "TOPICAL: TOPIC Pages AutomagicalLy."
- Grande-Ramírez, José Roberto; Roldán-Reyes, Eduardo; Aguilar-Lasserre, Alberto A. ;. Juárez-Martínez, Ulises. 2022. "Integration of Sentiment Analysis of Social Media in the Strategic Planning Process to Generate the Balanced Scorecard." *Applied Sciences* 12(23):12307–12307. doi: 10.3390/app122312307.
- Grimmer, Justin, and Brandon M. Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." *Political Analysis* 21(3):267–97. doi: 10.1093/pan/mps028.
- Grootendorst, Maarten. 2022. "BERTopic: Neural Topic Modeling with a Class-Based TF-IDF Procedure."
- Guizani, Khelil, and Sghaier Guizani. 2020. "IoT Healthcare Monitoring Systems Overview for Elderly Population." Pp. 2005–9 in *2020 International Wireless Communications and Mobile Computing (IWCMC)*. Limassol, Cyprus: IEEE.
- Guo, Jiafeng, Yinqiong Cai, Yixing Fan, Fei Sun, Ruqing Zhang, and Xueqi Cheng. 2022. "Semantic Models for the First-Stage Retrieval: A Comprehensive Review." *ACM Transactions on Information Systems* 40(4):1–42. doi: 10.1145/3486250.
- Haddaway, Neal R., Matthew J. Grainger, and Charles T. Gray. 2022. "Citationchaser: A Tool for Transparent and Efficient Forward and Backward Citation Chasing in Systematic Searching." *Research Synthesis Methods* 13(4):533–45. doi: 10.1002/jrsm.1563.
- Hadighi, S. Ali; Sahebjamnia, Navid; Mahdavi, Iraj; Shirazi, Mohsen Akbarpour. 2013. "A Framework for Strategy Formulation Based on Clustering Approach: A Case Study in a Corporate Organization." *Knowledge-Based Systems* 49(NA):37–49. doi: 10.1016/j.knosys.2013.04.008.
- Han, Mintak; Geum, Youngjung. 2022. "Roadmapping for Data: Concept and Typology of Data-Integrated Smart-Service Roadmaps." *IEEE Transactions on Engineering Management* 69(1):142–54. doi: 10.1109/tem.2020.3013295.

- Hannigan, Timothy R., Richard F. J. Haans, Keyvan Vakili, Hovig Tchalian, Vern L. Glaser, Milo Shaoqing Wang, Sarah Kaplan, and P. Devereaux Jennings. 2019. "Topic Modeling in Management Research: Rendering New Theory from Textual Data." *Academy of Management Annals* 13(2):586–632. doi: 10.5465/annals.2017.0099.
- Hassan Zadeh, A., and A. Jeyaraj. 2018. "Alignment of Business and Social Media Strategies: Insights from a Text Mining Analysis." *Journal of Business Analytics* 1(2):117–34. doi: 10.1080/2573234X.2019.1602002.
- Helfat, Constance E., Aseem Kaul, David J. Ketchen, Jay B. Barney, Olivier Chatain, and Harbir Singh. 2023. "Renewing the Resource-based View: New Contexts, New Concepts, and New Methods." *Strategic Management Journal* 44(6):1357–90. doi: 10.1002/smj.3500.
- Hirose, Yuta, Robert Phaal, Clare Farrukh, Nathasit Gerd Sri, and Sungjoo Lee. 2020. "Characterizing Maturity Levels for Organization-Wide Roadmapping Implementation." *IEEE Engineering Management Review* 48(4):133–43. doi: 10.1109/EMR.2020.3020547.
- Holloway, Clark. 1983. "Strategic Management and Artificial Intelligence." *Long Range Planning* 16(5):89–93. doi: 10.1016/0024-6301(83)90082-1.
- Huang, Lu, Xiang Chen, Xingxing Ni, Jiarun Liu, Xiaoli Cao, and Changtian Wang. 2021. "Tracking the Dynamics of Co-Word Networks for Emerging Topic Identification." *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE* 170.
- Huang, Ming-Hui; Rust, Roland T. ; Maksimovic, Vojislav. 2019. "The Feeling Economy: Managing in the Next Generation of Artificial Intelligence (AI)." *California Management Review* 61(4):43–65. doi: 10.1177/0008125619863436.
- Jeong, Yujin, Hyejin Jang, and Byungun Yoon. 2021. "Developing a Risk-Adaptive Technology Roadmap Using a Bayesian Network and Topic Modeling under Deep Uncertainty." *Scientometrics* 126(5):3697–3722. doi: 10.1007/s11192-021-03945-8.
- Jiang, Fei; Jiang, Yong; Zhi, Hui; Dong, Yi; Li, Hao; Ma, Sufeng; Wang, Yilong; Dong, Qiang; Shen, Haipeng; Wang, Yongjun. 2017. "Artificial Intelligence in Healthcare: Past, Present and Future." *Stroke and Vascular Neurology* 2(4):230–43. doi: 10.1136/svn-2017-000101.
- Kajikawa, Yuya; Takeda, Yoshiyuki; Matsushima, Katsumori. 2010. "Computer-assisted Roadmapping: A Case Study in Energy Research." *Foresight* 12(2):4–15. doi: 10.1108/14636681011035726.
- Kapoor, Rahul, and Daniel Wilde. 2023. "Peering into a Crystal Ball: Forecasting Behavior and Industry Foresight." *Strategic Management Journal* 44(3):704–36. doi: 10.1002/smj.3450.

- Kar, Sudatta, Arpan Kumar Kar, and Manmohan Prasad Gupta. 2021. "Modeling Drivers and Barriers of Artificial Intelligence Adoption: Insights from a Strategic Management Perspective." *INTELLIGENT SYSTEMS IN ACCOUNTING FINANCE & MANAGEMENT* 28(4):217–38.
- Kayabay, Kerem; Gökalp, Mert Onuralp; Gökalp, Ebru; Eren, P. Erhan; Koçyiğit, Altan. 2022. "Data Science Roadmapping: An Architectural Framework for Facilitating Transformation towards a Data-Driven Organization." *Technological Forecasting and Social Change* 174(NA):121264-NA. doi: 10.1016/j.techfore.2021.121264.
- Kayser, Victoria; Blind, Knut. 2017. "Extending the Knowledge Base of Foresight: The Contribution of Text Mining." *Technological Forecasting and Social Change* 116(NA):208–15. doi: 10.1016/j.techfore.2016.10.017.
- Keding, Christoph. 2020. "Understanding the Interplay of Artificial Intelligence and Strategic Management: Four Decades of Research in Review." *Management Review Quarterly* 71(1):91–134. doi: 10.1007/s11301-020-00181-x.
- Kenton, Zachary, Tom Everitt, Laura Weidinger, Iason Gabriel, Vladimir Mikulik, and Geoffrey Irving. 2021. "Alignment of Language Agents."
- Kerr, Clive; Phaal, Robert. 2020. "Technology Roadmapping: Industrial Roots, Forgotten History and Unknown Origins." *Technological Forecasting and Social Change* 155(NA):119967-NA. doi: 10.1016/j.techfore.2020.119967.
- Kerr, Clive, and Robert Phaal. 2022a. "Roadmapping and Roadmaps: Definition and Underpinning Concepts." *IEEE Transactions on Engineering Management* 69(1):6–16. doi: 10.1109/TEM.2021.3096012.
- Kerr, Clive, and Robert Phaal. 2022b. "Roadmapping and Roadmaps: Definition and Underpinning Concepts." *IEEE Transactions on Engineering Management* 69(1):6–16. doi: 10.1109/TEM.2021.3096012.
- Kerr, Clive; Phaal, Robert; Probert, David. 2011. "Cogitate, Articulate, Communicate: The Psychosocial Reality of Technology Roadmapping and Roadmaps." *R&D Management* 42(1):1–13. doi: 10.1111/j.1467-9310.2011.00658.x.
- Khademi, Behrooz, Hannele Lampela, and Kosmas X. Smyrniotis. 2021. "A Roadmap for Systematically Identifying Opportunities in Ecosystems Using Scientific Publications Data." *TECHNOLOGY INNOVATION MANAGEMENT REVIEW* 11(1):34–55.
- Khong, PW, and KS Lim. 2000. "Management of Technology: Employing Artificial Intelligence in Strategic Planning and Design." *INTERNATIONAL JOURNAL OF COMPUTER APPLICATIONS IN TECHNOLOGY* 13(3–5):98–106.

- Kim, Jieun; Park, Yongtae; Lee, Youngjo. 2016. "A Visual Scanning of Potential Disruptive Signals for Technology Roadmapping: Investigating Keyword Cluster, Intensity, and Relationship in Futuristic Data." *Technology Analysis & Strategic Management* 28(10):1225–46. doi: 10.1080/09537325.2016.1193593.
- Kim, Junhan; Geum, Youngjung. 2021. "How to Develop Data-Driven Technology Roadmaps: The Integration of Topic Modeling and Link Prediction." *Technological Forecasting and Social Change* 171(NA):120972-NA. doi: 10.1016/j.techfore.2021.120972.
- Kiron, David, and Michael Schrage. 2019. "Strategy For and With AI." *MIT SLOAN MANAGEMENT REVIEW* 60(4):30+.
- Klatt, Tobias; Schlaefke, Marten; Moeller, Klaus. 2011. "Integrating Business Analytics into Strategic Planning for Better Performance." *Journal of Business Strategy* 32(6):30–39. doi: 10.1108/02756661111180113.
- Kostoff, Ronald N. ; Geisler, Eliezer. 1999. "Strategic Management and Implementation of Textual Data Mining in Government Organizations." *Technology Analysis & Strategic Management* 11(4):493–525. doi: 10.1080/095373299107302.
- Kostoff, Ronald N. ; Schaller, R. R. 2001. "Science and Technology Roadmaps." *IEEE Transactions on Engineering Management* 48(10):132–43.
- von Krogh, Georg. 2018. "Artificial Intelligence in Organizations: New Opportunities for Phenomenon-Based Theorizing." *Academy of Management Discoveries* 4(4):404–9. doi: 10.5465/amd.2018.0084.
- Kunc, Martin, and Frances A. O'Brien. 2019. "The Role of Business Analytics in Supporting Strategy Processes: Opportunities and Limitations." *JOURNAL OF THE OPERATIONAL RESEARCH SOCIETY* 70(6):974–85.
- Kwon, Koopo; Jun, Sungchan; Lee, Yong-Jae; Choi, Sanghei; Lee, Chulung. 2022. "Logistics Technology Forecasting Framework Using Patent Analysis for Technology Roadmap." *Sustainability* 14(9):5430–5430. doi: 10.3390/su14095430.
- Kwon, Naae, Yuenkyung Yoo, and Byunghan Lee. 2024. "Novel Curriculum Learning Strategy Using Class-Based TF-IDF for Enhancing Personality Detection in Text." *IEEE Access* 12:87873–82. doi: 10.1109/ACCESS.2024.3417180.
- Kyrylov, Volodymyr, and Dmytro Chaplynskyi. 2023. "GPT-2 Metadata Pretraining Towards Instruction Finetuning for Ukrainian." Pp. 32–39 in *Proceedings of the Second Ukrainian Natural Language Processing Workshop (UNLP)*. Dubrovnik, Croatia: Association for Computational Linguistics.

- Lan Fang, Mei. 2022. "Future of AgeTech: Transdisciplinary Considerations for Equity, Intersectionality, Sustainability, and Social Justice." Pp. 536–41 in *Proceedings of the 15th International Conference on Pervasive Technologies Related to Assistive Environments*. Corfu Greece: ACM.
- Lazaridou, Angeliki, Elena Gribovskaya, Wojciech Stokowiec, and Nikolai Grigorev. 2022. "Internet-Augmented Language Models through Few-Shot Prompting for Open-Domain Question Answering."
- Lee, Min Kyung. 2018. "Understanding Perception of Algorithmic Decisions: Fairness, Trust, and Emotion in Response to Algorithmic Management." *Big Data & Society* 5(1):205395171875668-NA. doi: 10.1177/2053951718756684.
- Lee, Sungjoo; Lee, Seonghoon; Seol, Hyeonju; Park, Yongtae. 2008. "Using Patent Information for Designing New Product and Technology: Keyword Based Technology Roadmapping." *R&D Management* 38(2):169–88. doi: 10.1111/j.1467-9310.2008.00509.x.
- Lee, Sungjoo; Park, Yongtae. 2005. "Customization of Technology Roadmaps According to Roadmapping Purposes: Overall Process and Detailed Modules." *Technological Forecasting and Social Change* 72(5):567–83. doi: 10.1016/j.techfore.2004.11.006.
- Lee, Sungjoo; Yoon, Byungun; Lee, Changyong; Park, Jinwoo. 2009. "Business Planning Based on Technological Capabilities: Patent Analysis for Technology-Driven Roadmapping." *Technological Forecasting and Social Change* 76(6):769–86. doi: 10.1016/j.techfore.2009.01.003.
- Lei Wu, Steven C. H. Hoi, and Nenghai Yu. 2010. "Semantics-Preserving Bag-of-Words Models and Applications." *IEEE Transactions on Image Processing* 19(7):1908–20. doi: 10.1109/TIP.2010.2045169.
- Lewis, Patrick, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2021. "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks."
- Li, Xiang; Ang, Cheng Leong. 1997. "An Intelligent Scenario Generator for Strategic Business Planning." *Computers in Industry* 34(3):261–69. doi: 10.1016/s0166-3615(97)00062-6.
- Li, Xin; Xie, Qianqian; Jiang, Jiaojiao; Zhou, Yuan; Huang, Lucheng. 2019. "Identifying and Monitoring the Development Trends of Emerging Technologies Using Patent Analysis and Twitter Data Mining: The Case of Perovskite Solar Cell Technology." *Technological Forecasting and Social Change* 146(NA):687–705. doi: 10.1016/j.techfore.2018.06.004.
- Lichtenthaler, Ulrich. 2020. "Beyond Artificial Intelligence: Why Companies Need to Go the Extra Step." *Journal of Business Strategy* 41(1):19–26. doi: 10.1108/jbs-05-2018-0086.

- Liu, Nelson F., Kevin Lin, John Hewitt, Ashwin Paranjape, Michele Bevilacqua, Fabio Petroni, and Percy Liang. 2024. "Lost in the Middle: How Language Models Use Long Contexts."
- Loper, E., and S. Bird. 2002. "NLTK: The Natural Language Toolkit." Pp. 63–70 in *Proceedings of the ACL-02 Workshop on Effective Tools and Methodologies for Teaching Natural Language Processing and Computational Linguistics*.
- Ma. 2023. "Voyage Embeddings." *Voyage AI*. Retrieved August 27, 2024 (<https://blog.voyageai.com/2023/10/29/voyage-embeddings/>).
- Macis, Daniel, Sara Perilli, and Cristina Gena. 2022. "Employing Socially Assistive Robots in Elderly Care." Pp. 130–38 in *Adjunct Proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization*. Barcelona Spain: ACM.
- Massel, M. S. 1945. "Reappraisal of Depreciation and Obsolescence." *Proceedings of the Annual Conference on Taxation under the Auspices of the National Tax Association* 85–96.
- McInnes, Leland, John Healy, and Steve Astels. 2017. "Hdbscan: Hierarchical Density Based Clustering." *The Journal of Open Source Software* 2(11):205. doi: 10.21105/joss.00205.
- McInnes, Leland; Healy, John; Saul, Nathaniel; Großberger, Lukas. 2018. "UMAP: Uniform Manifold Approximation and Projection." *Journal of Open Source Software* 3(29):861-NA. doi: 10.21105/joss.00861.
- Miao, Hong; Wang, Yan; Li, Xin; Wu, Feifei. 2022. "Integrating Technology-Relationship-Technology Semantic Analysis and Technology Roadmapping Method: A Case of Elderly Smart Wear Technology." *IEEE Transactions on Engineering Management* 69(1):262–78. doi: 10.1109/tem.2020.2970972.
- Miric, Milan, Nan Jia, and Kenneth G. Huang. 2022. "Using Supervised Machine Learning for Large-scale Classification in Management Research: The Case for Identifying Artificial Intelligence Patents." *Strategic Management Journal* 44(2):491–519. doi: 10.1002/smj.3441.
- Mitchell, Melanie. 2019. "Artificial Intelligence Hits the Barrier of Meaning." *Information* 10(2):51-NA. doi: 10.3390/info10020051.
- Moayer, S. ;. Bahri, Parisa A. 2009. "Hybrid Intelligent Scenario Generator for Business Strategic Planning by Using ANFIS." *Expert Systems with Applications* 36(4):7729–37. doi: 10.1016/j.eswa.2008.09.046.
- Mortara, L., R. Phaal, C. Kerr, C. Farrukh, and D. Probert. 2014. "Tool Fingerprinting: Characterising Management Tools."
- Muennighoff, Niklas, Nouamane Tazi, Loïc Magne, and Nils Reimers. 2023. "MTEB: Massive Text Embedding Benchmark."

- Nazarenko, Anastasia; Vishnevskiy, Konstantin; Meissner, Dirk; Daim, Tugrul U. 2022. "Applying Digital Technologies in Technology Roadmapping to Overcome Individual Biased Assessments." *Technovation* 110(NA):102364-NA. doi: 10.1016/j.technovation.2021.102364.
- Okagbue, Hilary I., and Jaime A. Teixeira Da Silva. 2020. "Correlation between the CiteScore and Journal Impact Factor of Top-Ranked Library and Information Science Journals." *Scientometrics* 124(1):797–801. doi: 10.1007/s11192-020-03457-x.
- Oliveira, Maicon G., Robert Phaal, Glauco H. S. Mendes, Karina M. Serrano, and Camila Favoretto. 2023. "Dawn of Digital Roadmapping." *Research-Technology Management* 66(1):41–52. doi: 10.1080/08956308.2022.2130626.
- Oliveira, Maicon, Youngjung Geum, Rob Phaal, and Priscila Grison. 2023. "ROADMAPPING: DIMENSIONS AND LEVELS OF DIGITALISATION." *The Journal of the Korea Institute of Electronic Communication Sciences*.
- Oliveira, Maicon Gouvêa, Michèle Routley, and Robert Phaal. 2022. "The Digitalisation of Roadmapping Workshops." *Journal of Engineering and Technology Management* 65:101694. doi: 10.1016/j.jengtecman.2022.101694.
- Onan, A., V. Bal, and B. Y. Bayam. 2016. "The Use of Data Mining for Strategic Management: A Case Study on Mining Association Rules in Student Information System [Upotreba Rudarenja Podataka u Strateškom Menadžmentu: Analiza Slučaja Upotrebe Pravila Pridruživanja Rudarenja Podataka u Informacijskom Sustavu Podataka o Studentima]." *Croatian Journal of Education* 18(1):41–70. doi: 10.15516/cje.v18i1.1471.
- OpenAI. 2023. "GPT-4 Technical Report." doi: 10.48550/ARXIV.2303.08774.
- OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu,

Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O’Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine B. Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, C. J. Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. 2024. “GPT-4 Technical Report.”

Orsini, Jean-Francois. 1986. “Artificial Intelligence: A Way through the Strategic Planning Crisis?” *Long Range Planning* 19(4):71–77. doi: 10.1016/0024-6301(86)90273-6.

Orwig, Richard; Chen, Hsinchun; Vogel, Douglas R. ; Nunamaker, Jay F. 1997. “A Multi-Agent View of Strategic Planning Using Group Support Systems and Artificial Intelligence.” *Group Decision and Negotiation* 6(1):37–59. doi: 10.1023/a:1008636524765.

O’Sullivan, Eoin, Rob Phaal, University of Cambridge, Charles Featherston, and UK Government Office of Science. 2021. “Agile Roadmapping: An Adaptive Approach to

- Technology Foresight.” *Foresight and STI Governance* 15(2):65–81. doi: 10.17323/2500-2597.2021.2.65.81.
- Ozcan, Sercan; Homayounfard, Amir; Simms, Chris; Wasim, Jahangir. 2022. “Technology Roadmapping Using Text Mining: A Foresight Study for the Retail Industry.” *IEEE Transactions on Engineering Management* 69(1):228–44. doi: 10.1109/tem.2021.3068310.
- Park, Hyunkyun; Phaal, Robert; Ho, Jae Yun; O’Sullivan, Eoin. 2020. “Twenty Years of Technology and Strategic Roadmapping Research: A School of Thought Perspective.” *Technological Forecasting and Social Change* 154(NA):119965–NA. doi: 10.1016/j.techfore.2020.119965.
- Pennington, Jeffrey, Richard Socher, and Christopher Manning. 2014. “Glove: Global Vectors for Word Representation.” Pp. 1532–43 in *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Doha, Qatar: Association for Computational Linguistics.
- Perianes-Rodriguez, Antonio, Ludo Waltman, and Nees Jan van Eck. 2016. “Constructing Bibliometric Networks: A Comparison between Full and Fractional Counting.” *Journal of Informetrics* 10(4):1178–95. doi: 10.1016/j.joi.2016.10.006.
- Phaal, Robert; Farrukh, Cjp; Probert, David. 2007. “Strategic Roadmapping: A Workshop-Based Approach for Identifying and Exploring Strategic Issues and Opportunities.” *Engineering Management Journal* 19(1):3–12. doi: 10.1080/10429247.2007.11431716.
- Phaal, Robert, Clare Farrukh, and David Probert. 2004. “Technology Roadmapping—A Planning Framework for Evolution and Revolution.” *Technological Forecasting and Social Change* 71(1–2):5–26. doi: 10.1016/s0040-1625(03)00072-6.
- Phan, Phillip H. ; Wright, Mike; Lee, Soo-Hoon. 2017. “Of Robots, Artificial Intelligence, and Work.” *Academy of Management Perspectives* 31(4):253–55. doi: 10.5465/amp.2017.0199.
- Phan, The-Vinh; Nguyen, Hong-Quang; Nguyen, Hoang-Minh. 2015. “iiWAS - Multi-Layered Semantic Search for Open Innovation Needs.” *Proceedings of the 17th International Conference on Information Integration and Web-Based Applications & Services* NA(NA):5–NA. doi: 10.1145/2837185.2837214.
- Piccirillo, Isabela Neto, Daniel Capaldo Amaral, Maicon Gouveia de Oliveira, and Eduardo Bellini Ferreira. 2022. “Digital Roadmapping in the Pandemic: Lessons from Collaboration in the Glass Industry.” *Technology Analysis & Strategic Management* 1–15. doi: 10.1080/09537325.2022.2061344.

- Pinson, Suzanne; Moraĭtis, Pavlos. 1997. "An Intelligent Distributed System for Strategic Decision Making." *Group Decision and Negotiation* 6(1):77–108. doi: 10.1023/a:1008640625674.
- Pora, Ummaporn; Gerdri, Nathasit; Thawesaengskulthai, Natcha; Triukose, Sipat. 2022. "Data-Driven Roadmapping (DDRM): Approach and Case Demonstration." *IEEE Transactions on Engineering Management* 69(1):209–27. doi: 10.1109/tem.2020.3005341.
- Pora, Ummaporn; Thawesaengskulthai, Natcha; Gerdri, Nathasit; Triukose, Sipat. 2018. "Data-Driven Roadmapping Turning Challenges into Opportunities." *2018 Portland International Conference on Management of Engineering and Technology (PICMET)* NA(NA):NA-NA. doi: 10.23919/picmet.2018.8481975.
- Prolochs, Nicolas, and Stefan Feuerriegel. 2020. "Business Analytics for Strategic Management: Identifying and Assessing Corporate Challenges via Topic Modeling." *INFORMATION & MANAGEMENT* 57(1, SI).
- Rädiker, Stefan, and Udo Kuckartz. 2020. *Focused Analysis of Qualitative Interviews with MAXQDA*. 1st ed. DE: MAXQDA Press.
- Ranjan, Jayanthi. 2008. "Business Justification with Business Intelligence." *VINE* 38(4):461–75. doi: 10.1108/03055720810917714.
- Reimers, Nils, and Iryna Gurevych. 2019. "Sentence-BERT: Sentence Embeddings Using Siamese BERT-Networks." Pp. 3980–90 in *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. Hong Kong, China: Association for Computational Linguistics.
- Rojas, Claudia Vásquez; Reyes, Eduardo Roldán; Aguirre y Hernández, Fernando; Robles, Guillermo Cortés. 2018. "Integration of a Text Mining Approach in the Strategic Planning Process of Small and Medium-Sized Enterprises." *Industrial Management & Data Systems* 118(4):745–64. doi: 10.1108/imds-01-2017-0029.
- Rubeis, Giovanni, Mei Lan Fang, and Andrew Sixsmith. 2022. "Equity in AgeTech for Ageing Well in Technology-Driven Places: The Role of Social Determinants in Designing AI-Based Assistive Technologies." *Science and Engineering Ethics* 28(6):49. doi: 10.1007/s11948-022-00397-y.
- Rupprecht, Patrick, and Walter Mayrhofer. 2024. "Hybrid Intelligence - An Approach towards the Symbiosis of Artificial and Human Creativity and Interaction in the Design and Innovation Process in SMEs."
- SBERT.net. 2023. "Pretrained Models — Sentence-Transformers Documentation." Retrieved June 2, 2023 (https://www.sbert.net/docs/pretrained_models.html).

- Shamseer, L., D. Moher, M. Clarke, D. Ghera, A. Liberati, M. Petticrew, P. Shekelle, L. A. Stewart, and the PRISMA-P Group. 2015. "Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) 2015: Elaboration and Explanation." *BMJ* 349(jan02 1):g7647–g7647. doi: 10.1136/bmj.g7647.
- Simon, Herbert Alexander. 1968. *The Sciences of the Artificial*. 3. ed., [Nachdr.]. Cambridge, Mass.: MIT Press.
- Singh, Shruti, and Mayank Singh. 2024. "COSAEMB: Contrastive Section-Aware Aspect Embeddings for Scientific Articles."
- Sixsmith, Judith Agnes. 2022. "Key Ethical Challenges in the AgeTech Sector." Pp. 532–35 in *Proceedings of the 15th International Conference on Pervasive Technologies Related to Assistive Environments*. Corfu Greece: ACM.
- Son, Changho, Jieun Kim, and Youngjun Kim. 2020. "Developing Scenario-Based Technology Roadmap in the Big Data Era: An Utilisation of Fuzzy Cognitive Map and Text Mining Techniques." *TECHNOLOGY ANALYSIS & STRATEGIC MANAGEMENT* 32(3):272–91.
- Stewart, Geoffrey, and Mahmood Al-Khassawneh. 2022. "An Implementation of the HDBSCAN* Clustering Algorithm." *Applied Sciences* 12(5):2405. doi: 10.3390/app12052405.
- Tkáč, Michal; Verner, Robert. 2016. "Artificial Neural Networks in Business." *Applied Soft Computing* 38(38):788–804. doi: 10.1016/j.asoc.2015.09.040.
- Trevisan, Adriana Hofmann, Ana Lobo, Daniel Guzzo, Leonardo Augusto De Vasconcelos Gomes, and Janaina Mascarenhas. 2023. "Barriers to Employing Digital Technologies for a Circular Economy: A Multi-Level Perspective." *Journal of Environmental Management* 332:117437. doi: 10.1016/j.jenvman.2023.117437.
- Trujillo-Cabezas, R. 2021. "A Hybrid Fuzzy Modeling Method to Improve the Strategic Scenarios Design.: Integrating Artificial Intelligence Algorithms and the Field of Futures Studies Methods." in *Iberian Conference on Information Systems and Technologies, CISTI*, edited by M. J. Rocha A. Goncalves R. ,. Penalvo F. G. IEEE Computer Society.
- Trujillo-Cabezas, R. 2022. "A Non-Linear Scenario Plotting to Guide Strategists. A Hybrid Model between Foresight and Computational Intelligence Methods." in *Iberian Conference on Information Systems and Technologies, CISTI*. Vols. 2022-June, edited by G. R. Rocha A. Bordel B. ,. Penalvo F. G. IEEE Computer Society.
- Udo, Godwin J. 1998. "Artificial Neural Network: An Upcoming Strategic Decision Planning Support Tool."
- Vishnevskiy, Konstantin; Karasev, Oleg; Meissner, Dirk. 2015. "Integrated Roadmaps and Corporate Foresight as Tools of Innovation Management: The Case of Russian

- Companies.” *Technological Forecasting and Social Change* 90(2):433–43. doi: 10.1016/j.techfore.2014.04.011.
- Vukanti, Vidya; Jose, Anu. 2021. “Business Analytics: A Case-Study Approach Using LDA Topic Modelling.” *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)* NA(NA):1818–23. doi: 10.1109/iccmc51019.2021.9418344.
- Wang, Tai-Yue; Chien, Shih Chien. 2006. “Forecasting Innovation Performance via Neural Networks—a Case of Taiwanese Manufacturing Industry.” *Technovation* 26(5):635–43. doi: 10.1016/j.technovation.2004.11.001.
- Wang, Xinyi; Zeng, Deming; Dai, Haiwen; Zhu, You. 2020. “Making the Right Business Decision: Forecasting the Binary NPD Strategy in Chinese Automotive Industry with Machine Learning Methods.” *Technological Forecasting and Social Change* 155(NA):120032-NA. doi: 10.1016/j.techfore.2020.120032.
- Weigand, Hans, Paul Johannesson, and Birger Andersson. 2021. “An Artifact Ontology for Design Science Research.” *Data & Knowledge Engineering* 133:101878. doi: 10.1016/j.datak.2021.101878.
- Wieringa, Roel J. 2014. *Design Science Methodology for Information Systems and Software Engineering*. Berlin, Heidelberg: Springer Berlin Heidelberg.
- Willyard, Charles H; McClees, Cheryl W. 1987. “Motorola’s Technology Roadmap Process.” *Research Management* 30(5):13–19. doi: 10.1080/00345334.1987.11757057.
- Yilmaz Eroglu, Duygu, and Kemal Kilic. 2017. “A Novel Hybrid Genetic Local Search Algorithm for Feature Selection and Weighting with an Application in Strategic Decision Making in Innovation Management.” *Information Sciences* 405:18–32. doi: 10.1016/j.ins.2017.04.009.
- Yoon, Byungun, and Robert Phaal. 2013. “Structuring Technological Information for Technology Roadmapping: Data Mining Approach.” *TECHNOLOGY ANALYSIS & STRATEGIC MANAGEMENT* 25(9):1119–37.
- Yoon, Byungun; Phaal, Robert; Probert, David. 2007. “Morphology Analysis for Technology Roadmapping: Application of Text Mining.” *R&D Management* 38(1):51–68. doi: 10.1111/j.1467-9310.2007.00493.x.
- Yoon, Y. 1999. “Discovering Knowledge in Corporate Databases.” *INFORMATION SYSTEMS MANAGEMENT* 16(2):64–71.
- Zhang, Hao; Daim, Tugrul U. ; Zhang, Yunqiu. 2021. “Integrating Patent Analysis into Technology Roadmapping: A Latent Dirichlet Allocation Based Technology Assessment and Roadmapping in the Field of Blockchain.” *Technological Forecasting and Social Change* 167(NA):120729-NA. doi: 10.1016/j.techfore.2021.120729.

- Zhang, Yi; Guo, Ying; Wang, Xuefeng; Zhu, Donghua; Porter, Alan L. 2013. "A Hybrid Visualisation Model for Technology Roadmapping: Bibliometrics, Qualitative Methodology and Empirical Study." *Technology Analysis & Strategic Management* 25(6):707–24. doi: 10.1080/09537325.2013.803064.
- Zhang, Yi, Guangquan Zhang, Hongshu Chen, Alan L. Porter, Donghua Zhu, and Jie Lu. 2016. "Topic Analysis and Forecasting for Science, Technology and Innovation: Methodology with a Case Study Focusing on Big Data Research." *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE* 105:179–91.
- Zhang, Yi; Zhou, Xiao; Porter, Alan L. ;. Gomila, Jose M. Vicente. 2014. "How to Combine Term Clumping and Technology Roadmapping for Newly Emerging Science & Technology Competitive Intelligence: Problem & Solution Pattern Based Semantic TRIZ Tool and Case Study." *Scientometrics* 101(2):1375–89. doi: 10.1007/s11192-014-1262-2.
- Zhu, Junwen, and Weishu Liu. 2020. "A Tale of Two Databases: The Use of Web of Science and Scopus in Academic Papers." *Scientometrics* 123(1):321–35. doi: 10.1007/s11192-020-03387-8.

8. APPENDIX 1: Exploratory data gathering with roadmapping practitioners

This Appendix outlines the process of collecting primary data from roadmapping practitioners to understand current practices and challenges in implementing roadmapping processes. The research engages with professionals with experience in strategic roadmapping across various industries to gather insights on how roadmapping is conducted in practice, the extent of digital tool adoption, and the potential for AI integration. This exploratory approach complements the systematic literature review by providing practical context to the theoretical frameworks discussed earlier.

8.1.1. EXPLORATORY DATA GATHERING

Drawing on these comprehensive insights about roadmapping digitalization, the following section presents an exploratory data gathering with practitioners. The exploratory data gathering targets organizations incorporating roadmapping in their strategic planning processes and advancing their practices through digital roadmapping implementation. The exploratory data gathering aims to provide further granularity on the real-world application of these theories and practices, contributing to a richer and more practical understanding of roadmapping digitalization to serve as a background of reference for our artifact development. Results from the exploratory data gathering can be seen in Appendix 1.

How long have you been working with roadmapping?

- Less than 1 year
- More than 1 and less than 3 years
- More than 3 and less than 5 years
- Between 5 and 10 years
- More than 10 years

How would you rank your experience with roadmapping?

- Very low
- Low
- Average
- High

- Very high

Likert scale, from -3 to +3, Strongly Disagree to Strongly Agree:

Construct 1: Stage of roadmapping implementation, maturity level.

1. The organization has already started exploring the possibility of applying roadmapping for technology and strategic planning.
2. The organization decided to use roadmapping.
3. The organization has trained the operation team to understand the analysis steps and required tools used for developing a roadmap.
4. The roadmaps have been developed and used in the organization, but they are still within certain units or departments.
5. The roadmapping activities have been fully integrated throughout the organization.
6. The organization has decided to take an active approach to sustain roadmapping implementation.

Construct 2: Roadmapping performance.

7. In your organization, knowledge related to roadmapping is effectively shared among team members.
8. There is consensus within the team in your organization when making decisions related to the roadmapping process.
9. Your organization efficiently manages information throughout the roadmapping implementation.
10. Your roadmapping process effectively prioritizes tasks, leading to better decision-making.
11. The roadmapping process in your organization demonstrated significant productivity.
12. The roadmapping process is agile.
13. All participants are actively engaged throughout the roadmapping implementation process.
14. The quality of the roadmap adheres to the highest standards.

Open question: What other aspects are related to the performance of roadmapping in your organization?

Construct 3: Visual nature of the roadmapping framework.

15. The visual nature of the roadmapping framework helps reveal patterns in the evidence.
16. The visual nature of the roadmapping framework helps reveal gaps in the evidence deserving further attention.
17. The visual nature of the roadmapping framework involved and engaged your imagination as a participant.
18. The visual nature of the roadmapping framework inspired motivation and identification with the roadmap.
19. The visual nature of the roadmapping framework can be considered as suited for convincing communication and presentation purposes.

Open question: In what additional manners is the visual aspect of roadmapping manifested or emphasized in your organization?

Construct 4: Data in roadmapping.

20. Data is used to support the traditional process of roadmapping.
21. Data helps mediate the market needs and technological innovations of the organization.
22. Data helps generate value, pushing for innovation development.

Open question: Beyond previously discussed methods, how is data utilized in the roadmapping process within your organization?

Construct 5: Digital Information management in the roadmapping process.

23. Analogue information is used in the roadmapping process.
24. Native digital information is used in the roadmapping process.
25. Digital information is managed in the roadmapping process.
26. Digital information is integrated and updated in the roadmapping process.

Construct 6: Landscaping in the roadmapping process.

27. People-based brainstorming is used in the roadmapping process.
28. Descriptive tools are used to search and collect supplementary information in the roadmapping process.
29. Predictive tools are used to envision and foresee topics in the roadmapping process.

30. Prescriptive tools are used to support strategy formulation in the roadmapping process.

Construct 7: Strategy formulation in the roadmapping process.

31. There were expert based connections in the roadmapping process.
32. Digital tools are used for topic connections in the roadmapping process.
33. Digital tools are used for multilayer connections in the roadmapping process.
34. Digital tools are used to define strategic narratives and priorities.

Construct 8: Social interaction in the roadmapping process.

35. There is collocated interaction with analogue information in the roadmapping process.
36. There is collocated interaction with digitized information in the roadmapping process.
37. There is remote interaction with digital information in the roadmapping process.
38. There is virtualized interaction with digital people and information in the roadmapping process.

Open question: Beyond the topics already addressed in this exploratory data gathering, are there any other insights you can provide regarding how digital tools are integrated with or influence the roadmapping process in your organization?

Final Section: Details About Your Organization

How many employees are in your organization?

- Less than 10
- Between 10 and 49
- Between 50 and 249
- Between 250 and 499
- Between 500 and 1999
- 2000 or more

Select the age bracket that corresponds to the number of years your organization has been in operation

- Less than 1 year
- More than 1 and less than 3 years

- More than 3 and less than 5 years
- Between 5 and 10 years
- More than 10 years

In which sector does your organization operate?

- Manufacturing
- Information and communication
- Services
- Electricity, gas, steam and air conditioning supply
- Public administration, social, security, education
- Mining, raw materials, water and waste
- Transportation and storage
- Agriculture, forestry, fishery
- Wholesale and retail trade, motor vehicle repair
- Construction and real state

What is your function in the organization?

- Technology and innovation management
- Strategic management and business development
- General management
- Pre-development, design, research and development
- Product management
- Project management
- Production, production planning
- Quality management, procurement, finance and controlling.
- Other

Open question: Please share any further comments or suggestions.

8.1.2. RESULTS OF THE EXPLORATORY DATA GATHERING

The data gathering targeting organizations that incorporate roadmapping in their strategic planning processes provided insights into the current state of roadmapping digitalization. A total

of 9 organizations participated in the data gathering, revealing patterns that inform our understanding of roadmapping implementation, performance, and digitalization challenges. The respondents' profiles showed varied experience levels with roadmapping, with 33.33% having less than 1 year of experience, 33.33% having 1-3 years, and the remaining participants having a longer experience range. Despite this varied experience, 33.33% rated their roadmapping experience as "Very high" and another 22.22% as "High".

When examining roadmapping implementation maturity, 55.56% of respondents strongly agreed that their organization had started exploring roadmapping for technology and strategic planning, and 44.44% strongly agreed they had decided to use roadmapping; agreement levels declined as implementation progressed toward full integration. Only 22.22% agreed that roadmapping activities had been integrated throughout their organization, with 11.11% strongly disagreeing. This pattern suggests that while roadmapping adoption is widespread, full implementation and integration remain challenging for some organizations.

Roadmapping performance metrics revealed both strengths and areas for improvement. Knowledge sharing effectiveness showed mixed results, with 33.33% strongly agreeing it was effective while 11.11% somewhat disagreed. Consensus in decision-making related to roadmapping appeared strong, with 77.77% at least somewhat agreed. However, information management throughout roadmapping implementation emerged as a potential pain point, with only 22.22% agreeing or strongly agreeing that it was efficient. Task prioritization, productivity, agility, and engagement all showed moderate success with room for improvement. The visual nature of the roadmapping framework received positive ratings. Over 80% of respondents at least somewhat agreed that visuals help reveal patterns and gaps in evidence, with 55.55% agreeing that the visual nature helps reveal patterns in the evidence. 88.88% agreed or strongly agreed that the visual nature engaged participants' imagination, suggesting that the visual framework remains one of roadmapping strongest assets, even as it evolves digitally.

Data usage in roadmapping showed recognition of its value, with 88.88% at least somewhat agreeing that data helps mediate market needs and technological innovations of the organization. All respondents (100%) at least somewhat agreed that data helps generate value, pushing for innovation development. This indicates high recognition of data's potential value in the roadmapping process. A contrast appeared when examining digital information management

in roadmapping. While 88.88% at least somewhat agree that analog information is used in the roadmapping process, only 33.33% agree that native digital information is used. Furthermore, only 33.33% at least somewhat agreed that digital information is managed effectively, and just 22.22% agreed that digital information is integrated and updated in the roadmapping process. This highlights a gap in digital information utilization and management.

The landscaping dimension of roadmapping showed continued reliance on traditional approaches. People-based brainstorming remains dominant (88.88% agree or strongly agree), while the use of descriptive tools (44.44% agreement), predictive tools (33.33% agreement), and prescriptive tools (22.22% agreement) for roadmapping showed lower adoption rates. This indicates traditional approaches still prevail over more advanced analytical methods. In strategy formulation, expert-based connections in roadmapping remain strong (77.77% agree or strongly agree). However, digital tools for topic connections (22.22% agreement), multilayer connections (22.22% agreement), and defining strategic narratives and priorities (11.11% agreement) showed minimal adoption. This reveals limited integration of digital tools in core strategy development processes.

Social interaction patterns in roadmapping followed similar trends. Collocated interaction with analog information is prevalent (55.55% agree or strongly agree), while collocated interaction with digitized information (11.11% agreement), remote interaction with digital information (22.22% agreement), and virtualized interaction with digital people and information (11.11% agreement) showed lower adoption rates. This suggests roadmapping remains an in-person, analog activity despite digital possibilities.

These findings validate the need for enhanced digital approaches in roadmapping while preserving its visual and collaborative strengths. The data reveals opportunities for AI augmentation in information management and strategy formulation, where digital adoption lags the most. The gap between recognition of data's value and actual implementation of digital approaches across dimensions of roadmapping points to potential barriers to roadmapping digitalization that could be addressed through AI-augmented solutions.

9. APPENDIX 2: BERTopic bibliometric analysis

Table 9 Topics extracted using BERTopic.

Count	Name	Keywords	Representative documents
1359	Business Performance Analytics and Evaluation	['data', 'experts', 'research', 'expert', 'quality', 'study', 'approach', 'information', 'databases', 'process']	['The constructions of interview questions consist of four sections namely: demographic data of the participants, business intelligence, business analytics, and performance management.3)Analysis Method: Data analysis of the interview was done by adopting the qualitative data analysis as suggested by .', 'While metrics studies provide the most obvious examples, this conclusion can be easily generalized to any of the evaluation methods.6.Selection of Evaluation Criteria. The sixth important factor, evaluation criteria, will depend on the interests of the audience for the evaluation, the nature of the benefits and impacts, the availability and quality of the underlying data, the accuracy

			and quality of results desired, the complementary criteria available and suites of diagnostic techniques desired for the complete analysis, the status of algorithms and analysis techniques, and the capabilities of the evaluation team.⁷ Reliability of Evaluation. The seventh important factor is reliability or repeatability.', 'Evaluation of the methods as proposed in this article as well as the data sources should be among the next steps.']
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866	Technology Roadmapping and Data-driven Development	['roadmap', 'roadmapping', 'roadmaps', 'technology', 'workshop', 'workshops', 'data', 'process', 'digital', 'development']	['The data analysis results can be effectively applied for each process of technology roadmapping, and final evaluation of technology roadmaps.', 'The research is based on a literature review of technology roadmapping, key success factors, and challenges to roadmap development and implementation in an organization.', 'The roadmap development method is also data-driven.']
536	Scenario Discovery in Decision Making	['scenario', 'scenarios', 'discovery', 'policy', 'cases', 'uncertainty', 'decision', 'futures', 'future', 'coverage']	['Scenario number two is the least recommended scenario.', 'Scenario discovery provides a set of analytic tools that help decision makers identify such scenarios by focusing on those futures most important to the design of and choice among candidate robust strategies.', 'Scenario number three and scenario number four are two transition scenarios that can go to

			scenario number one and/or scenario number two.']
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518	Organization al Knowledge in Complex Social Systems	['organization , 'organizations', 'information', 'systems', 'environment', 'knowledge', 'organizational', 'management', 'firms', 'journal']	['Doing this allows us to scrutinize the underlying social structures and processes organizations use to generate knowledge from their highly complex environment of different functional subsystems of society .', 'Importantly, organizations complex social environment consists of modern societies functional subsystems like politics, economy, science, and law.', 'According to social systems theory, a research organization is above all part of societies subsystem of science.']
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482	Strategic Planning and Management	['strategic', 'planning', 'strategy', 'plan', 'organization', 'management', 'managers', 'strategies', 'process', 'plans']	['Grievances Against Strategic PlanningThe complaints against strategic planning, according to a Business Week study ¹ of corporations which have extensive experience of the process, are as follows:the alienating behaviour of the strategic planning staff. the demands of the planning staff.the wrong predictions made by planners.fr the division created by planners between top management and line managers.the demands of the planning process. the impediment created by the planning process in adequately assessing the outside world.fr the rigidity of plans and their dangerous consequences.the simplistic nature of plans which makes corporate moves transparent to the competition and increases its vulnerability.inadequate contingency plans.the difficulty of implementing
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			plans.', 'One of the main management processes is the strategic planning process.', 'A.Strategic']
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394	AI Adoption in Organizational Strategy	['ai', 'adoption', 'barriers', 'solutions', 'drivers', 'intelligence', 'artificial', 'strategy', 'organizational', 'lack']	['We have formulated the following research questions to study the cause- effect relationship among AI adoption drivers and AI adoption barriers in business functions.', "As part of the AI adoption strategy, executive leadership must understand the current AI maturity and opportunities in the organization, the drivers and barriers to AI adoption, and focus on change management related to the impact on employees' roles and the cultural change .", 'RQ1: What are the driving factors and barriers to AI adoption in organizational strategy?RQ2: Among the driving factors of AI adoption in organizational strategy, what kind of hierarchical relationship exists?RQ3: Among the barriers to AI adoption in organizational strategy, what kind of hierarchical relationship exists?This study developed a total interpretive
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			structural model of drivers and barriers of AI adoption in organizational strategy to answer these research questions.']
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308	Emerging Technologies & Innovation Trends	['technology', 'development', 'technologies', 'technological', 'new', 'products', 'opportunities', 'market', 'emerging', 'trends']	[For practical technology development, technology trends and characteristics were identified, and areas with potential for technology development were derived .', 'Identifying future changing trends of these emerging technologies as early as possible based on the understanding of the innovation pathways of these emerging technologies is crucial for government and enterprise research and development strategic planning to gain a first-mover advantage in the competitive business environment .', 'Based on the analysis of different technological innovation pathways, we try to identify future trends in technology, function, products, and market with the help of domain experts.']
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298	Patent Analysis & Technological Advancements	['patent', 'patents', 'analysis', 'technological', 'technology', 'information', 'number', 'based', 'documents', 'citation']	['Patent analysis and patent commercialization.', 'In particular, the patent network is a network analysis based on patent data, and the relationship between patents is visualized and analyzed .', 'Moreover, the patent number means the number of patents firms applied in each year.']
291	Technology Roadmapping and Innovation Management	['trm', 'tdm', 'trms', 'ma', 'development', 'technologies', 'management', 'product', 'driven', 'market']	['the contributions of previous research using TRM to analyze TOA, data-driven TRM have some limitations in three areas: processing data data-driven TRM, identifying potential opportunities, and selecting the data source.', 'Regarding theory-based TRM, some previous studies have focused on the concept and process of TRM .', 'To support market-pull and technology-driven innovation, new frameworks for TRM have been proposed, such as T-Plan TRM , learning-based TRM , or umbrella-based TRM .In']

264	Agent Coordination & Blackboard Systems	['agents', 'agent', 'actions', 'subobjective', 'elementary', 'blackboard', 'subobjectives', 'action', 'level', 'specialist']	['The Compatibility Blackboard contains the set of feasible elementary actions proposed by all the Specialists Agents .', 'The blackboard control agent and the stakeholder agent are the most important agents within the system agents cluster.', 'The Domain Blackboard contains feasible elementary actions proposed by the Specialist Agents to achieve a subobjective .']
248	Feature Subset Selection and Weighting Algorithms	['feature', 'subset', 'selection', 'classification', 'hga', 'features', 'algorithm', 'accuracy', 'weighting', 'classifier']	['The first contribution is the novel HGA for the feature subset selection and the feature weighting problem.', 'A natural fitness function in feature subset selection and feature weighting is the classification accuracy.', 'However, it is also possible to use a simultaneous feature subset selection and feature weighting algorithm similar to the developed HGA for this purpose.']

237	Text Mining for Unstructured Data Analysis	['text', 'mining', 'foresight', 'textual', 'unstructured', 'data', 'methods', 'structured', 'information', 'web']	['Text mining can be defined as the process of obtaining information from text-based data.', 'Thus, for this work, the authors decided to build a customized text mining-framework based on Python and SQL.3.Using text mining for foresight. This section describes different textual data sources that are or that might be analyzed with text mining and outlines different applications that link text mining and foresight at a methodological level .3.1.Text', 'One of these objective analysis methods is text mining, and some scholars have introduced text mining into TRM , , , to support the decision-making process.']
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222	Group Brainstorming Stages	['comments', 'group', 'list', 'ideas', 'participants', 'brainstorming', 'stage', 'electronic', 'facilitator', 'divergent']	['Thus, far fewer comments in the electronic brainstorming output actually get linked to the items on the list generated by a group.', 'Divergence in a group setting means that members of the group provide comments or ideas concerning the topic at hand.', 'In order to develop this list of elements, group members need to browse the comments produced during the divergent stage of any of the three methods described.']
203	Link Prediction in Networks	['link', 'prediction', 'network', 'nodes', 'edges', 'centrality', 'node', 'links', 'connections', 'networks']	['We identify possible links between unconnected nodes based on link prediction.', 'Therefore, we identify possible links between unconnected nodes based on link prediction.', 'We identify possible links between unconnected nodes based on link prediction.']

175	Twitter Sentiment Analysis on Emerging Technologies	['twitter', 'sentiment', 'tweets', 'emerging', 'users', 'social', 'tweet', 'media', 'expectations', 'emergence']	["Through the data mining of tweets and Twitter users' attribute characteristics, we can study change characteristics of Twitter users' sense of, response to, and expectations for emerging technologies.", "We made a comparison analysis of the results of patent analysis and Twitter users' sense of and response to emerging technologies, and combined awareness information with Twitter users' expectations for the technologies and changes in the professional types of Twitter users and their topics of interest over time to identify development trends of emerging technologies.", "In this paper, we used sentiment 140 which is a Twitter sentiment analysis tool to mine Twitter users' emotional reaction to emerging technology contained in the tweets and to study the changing
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			characteristics of Twitter users' expectations of emerging technology over time."]
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175	Business Analytics in Strategic Decision-Making	['analytics', 'business', 'tools', 'strategy', 'evidence', 'support', 'descriptive', 'predictive', 'performance', 'strategic']	['There is some evidence of business analytics tools being combined with tools from other fields to support strategy.', 'We have discussed the emerging field of business analytics and illustrated how business analytics has been applied in practice.', 'Our research has found evidence within the literature that business analytics tools are being used to support activities within a strategy process; however there some gaps.']
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173	Artificial Neural Networks and Learning Algorithms	['output', 'training', 'error', 'neurons', 'neural', 'neuron', 'layer', 'input', 'learning', 'network']	['The topology of the Artificial Neural Networks model with 1 year of lead time is as follows :Input neurons: t - 1, I, I, I.Hidden neurons: four hidden neurons.', 'This comparison results in an error for each neuron in the output layer.', 'MLP is a specific architecture for a single hidden layer, two-input two- output neural network which is trained by the back- propagation learning algorithm.']
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164	BI Implementation and Analytics in Business Management	['bi', 'business', 'implementation', 'enterprise', 'implementing', 'analytics', 'management', 'data', 'performance', 'support']	['A successful BI ties business and information technology together to help enterprises manage and integrate ongoing investments in BI, allocate BI resources, prioritize projects, and minimize the risk associated with BI implementations.', 'this paper BI and the growing potential for implementing BI is explained.', 'Based on this, the objective of the current study are to conceptualize the implementation issues in the integration of BI and analytics, to identify the critical factors for the implementation of BI, analytics and organizational performance management, and to integrate BI, analytics and organizational performance management implementation factors.']
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150	Latent Dirichlet Allocation in Topic Modeling	['topic', 'topics', 'modeling', 'latent', 'modeling', 'model', 'dirichlet', 'lda', 'allocation', 'similarity']	['al. observed that Latent Dirichlet Allocation is the most popular approaches in topic modeling and also summarized the challenges in topic modeling.', 'Latent Dirichlet Allocation based topic modeling is used to cluster the topics by calculating the probability distribution over a set of words.', 'In addition, although in this paper, we only applied PCA analysis for the topic clustering studies, more new concepts and algorithms are introduced into ST&I text mining. Topic models is a significant one, which is based on the Latent Dirichlet Allocation algorithm and constructs a document-topic-word Bayesian model for potential topic understanding and retrieving.']
128	artificial intelligence Business Strategy	['et', 'artif', 'anal', 'bus', 'jin', 'zhao', 'cont', 'strat', 'raymond', 'vishnevskiy']	['et', 'Go et', 'et']

126	Keyword Extraction and Vector Construction	['keywords', 'keyword', 'document', 'search', 'occurrence', 'documents', 'words', 'frequency', 'vector', 'terms']	['The first step is to extract keywords from all documents and create keywords vectors of documents in the same manner as clustering.', '3. The matrix is divided into four quadrants: interactive keywords, causal keyword, family keywords, and unrelated keywords.1) Interactive quadrant is characterized by high confidence and high support for a certain keyword pair, implying that those two keywords have a high level of co-occurrence and a high level of dependency.', 'The final keyword list, after the two-step process, is listed in Table 5.4.3.Construction of keyword vector Based on the keywords, downloaded documents are then transferred to the keyword vector, more specifically; adocument-keyword vector in which the row consists of
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			documents and column consists of keywords.']
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122	Hierarchical Clustering and Centroid Analysis	['clusters', 'clustering', 'cluster', 'centroids', 'number', 'means', 'centroid', 'algorithm', 'record', 'similarity']	['A.Initialization: to set each record as a cluster;B.Iteration: to calculate similarity among clusters and group the two clusters with the highest similarity value;C.Terminal condition: to set the cluster number as the terminal condition, where a threshold will be used to illustrate the percentage of the cluster number in the record number.', 'These clusters are located in the sublevel of the clusters obtained in the first clustering step, generating a hierarchical structure of clusters.', 'In Table I, we show only the top nine clusters.']
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122	Phrase Frequency & Document Analysis	['frequency', 'phrases', 'phrase', 'document', 'word', 'documents', 'term', 'similarity', 'words', 'text']	['Phrase frequency analysis.', 'Rather than a few high frequency phrases to describe the area, many diverse low frequency phrases are used.', 'In the present DT approach, the taxonomies are generated by selecting many high frequency themes from the phrase frequency analysis, constructing a phrase frequency dictionary for each theme of phrases locate d physically close to the theme in the text, and then grouping related themes whose dictionaries contain more than a threshold number of shared phrases into categories.']
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120	Data Mining Techniques and Applications	['mining', 'data', 'patterns', 'useful', 'databases', 'dm', 'techniques', 'knowledge', 'discovery', 'time']	['Such a plan would address the role of textual data mining in the context of overall data mining, the role of the organizations overall data mining in the context of allied organizations data mining in similar technical areas, and how different types/ classes of technical experts should be integrated most efficiently into the data mining process.', 'Data cleaning aims to remove noisy, missing or inconsistent data from the data set; data integration aims to integrate multiple data sources; data selection aims to extract appropriate data from database; data transformation involves application of appropriate techniques so that data can be converted into a suitable form for mining task; data mining involves the application of data mining methods/algorithms to extract useful patterns; pattern evaluation aims to evaluate
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			the interestingness of extracted patterns, while knowledge presentation involves presenting the mined knowledge to the user in a visual form .Data', 'Data mining, also known as knowledge discovery in databases is the process of discovering interesting patterns in databases that are useful in decision making .']
120	TISM Analysis - Drivers and Barriers	['table', 'barriers', 'drivers', 'fgd', 'tism', 'shows', 'factors', 'cause', 'factor', 'digraph']	['Table 2.', 'Table 1.B', 'Table 3.']

106	Keyword Mapping and Relationships	['keyword', 'keywords', 'map', 'visibility', 'relational', 'relationship', 'maps', 'portfolio', 'treemap', 'relationships']	['In the keyword relational map, a 2- dimensional map is developed using support as an intra-layer affinity relationship and confidence as an inter-layer dependency relationship.3.3.5.1.Keyword portfolio map.', 'Using these variables two types of keyword intensity maps can be constructed as shown in Figure 4: keyword visibility map and keyword diffusion map.', 'After measuring each rule, two types of map are developed: a keyword portfolio map and a keyword relational map.']
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96	Citation Analysis & Bibliometrics	['citation', 'publications', 'papers', 'citations', 'journals', 'research', 'network', 'published', 'journal', 'number']	['We also analyzed the characteristics of each cluster by the titles and abstracts of papers that are frequently cited by the other papers in the cluster, as well as the journals in which the papers in the cluster were published.', 'No#TopicDescriptive Terms1#11open-access; information professionals; Linked Data; Linked Data;LIS scholars2#12scientometric indicators; leading position; citation impact; co-citation; citation behavior; citation analysis3#16image retrieval systems; image use; search tactics; video searchsystem; user preferences4#17research hotpots; informetrics; climate change; health care;5#18information seeking; information behavior; information sharing;information requirements; information sources6#20network
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			analysis; social network; information diffusion; treestructure; centrality measures⁷22social media; Altmetrics; blogs; Tweets; microblog⁸39semantic analysis; k-means; vector space model; F1-measure; latentsemantic analysis⁹41interdisciplinarity; subject categories; impact factor; SocialSciences; scientific activityNote: underlined terms were manually selected to label the corresponding topic.represents the number of predicted new edges matched to the real network after Gs3.4.Case study In this Section, the proposed framework is further analyzed in-depth on Information Science .', 'Citation network analysis is based on existing publications from the past to the present.']
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79	Organization al Goal-Factor Clustering for Departmental Strategies	['clusters', 'goals', 'cluster', 'departmental', 'strategies', 'factors', 'goal', 'clustering', 'factor', 'influential']	['After determining the integrated goal-factor clusters, organizational strategies are generated based on each cluster.', 'If the goals and factors of earlier goal- factor cluster match with the goals and factors of strategy- goal and strategy-factor clusters at this stage, then the model is valid.', 'Comparing strategy-goal and strategy- factor clusters with the factor- goal clusters show that goals and strategies in previous clusters again fall in the same clusters while the number of the clusters is decreased to five.']
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73	Meta-Intelligence in Organizational Transformation	['intelligence', 'meta', 'hi', 'types', 'renewal', 'transformation', 'recombination', 'transformations', 'ai', 'interdependencies']	['Without a strong meta-intelligence, firms may be unable to: ask the right questions for further developing the intelligence architecture, decide about the use of AI or HI and skills, ensure high usability of AI for the particular applications in the organization, initiate change processes to encourage open attitudes towards interacting with AI, adapt the intelligence architecture to incorporate new skills and expertise, and manage interdependencies and potential conflicts between various types of intelligence.', 'Here, a meta-intelligence, which contributes to steering the development and transformation of the two types of intelligence, will be critical.', 'Specifically, this meta-intelligence involves the renewal and recombination of the different types of intelligence, which is
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			comparable with the intertemporal evolution of organizational capabilities and innovation processes .First, the renewal of the two intelligence types may be needed due to advances in AI technology or the need for deepening and extending a firms HI to new fields.']
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72	Data-Integrated Smart Service Systems	['smart', 'service', 'services', 'data', 'integrated', 'systems', 'actors', 'ecosystems', 'works', 'maglio']	['That is, smart products can be recognized as a trigger for the development of new services .Considering the conceptual background and phenomena, smart service systems have the following distinctive characteristics.1)System components have been diversified, thus leading to increase the complexity of the system.2)User interaction through smart products with ICT is inevitable for value creation.3)Big data analytics has a crucial role in the smart service system.', 'Smart service roadmaps also have been suggested , , with frameworks and processes suitable for smart services.', 'Therefore, data-integrated smart service roadmapping is the process to support the long-term planning of smart services, with consideration of data requirements over time.']
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67	big data: Era, Challenges, and Opportunities	['big', 'data', 'cloud', 'era', 'techniques', 'scale', 'mathematics', 'large', 'privacy', 'software']	[Finally, we summarized several evolutionary trends and five big data issues ” software tools, techniques & algorithms, analytic scope, analytic capability, and data management, and identified four big data-related emerging topics, which would be considered as the future directions in the following decade.', 'Era of big data Big data□ refers to dataset whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze .', 'The availability of big data and scalable big data technologies have provided businesses with opportunities to utilize big data to gain a competitive advantage.']
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65	Patent Text Mining and Keyword Analysis	['patent', 'text', 'documents', 'mining', 'patents', 'keywords', 'keyword', 'analysis', 'word', 'abstracts']	['Thirdly, we suggest a possibility of extracting more information from patent documents using text-mining and data-mining techniques together with the conventional patent analysis techniques.', 'After TM has been used to extract keywords representing the contents of documents, they can be used to measure the similarity of patent documents or groups of patent documents .', 'Patent documents contain unstructured text information, and the network is analyzed by extracting key keywords through text mining techniques.']
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61	Layered Market, Product, and Technology Analysis	['layer', 'layers', 'sub', 'axis', 'market', 'technology', 'product', 'service', 'titanium', 'horizontal']	['The layers can be divided into technology, product, service and market layers, which are each listed above the previous layer.', 'The second step is layer mapping, which is related to defining and developing sub- layers for each market, product, and technology layer.', 'For example, the technical layer is divided into three sub-layers, from sub- layer S, sub-layer A to sub- layer O, along the vertical axis.']
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60	Morphologic al Analysis of Technology & Product Relationships	['morphology' , 'configurations', 'product', 'relationship', 'correlation', 'technology', 'matrix', 'morphological', 'products', 'module']	['However, because technological levels of the highest correlation value in the morphology matrix are selected, a level in some specific attributes can be chosen more than once, and on the contrary, a level in other attributes might not be linked into any level in product morphology.', 'Therefore, all levels of product morphology must have a unique relationship with technology morphology.2.The second step is to examine technological requirements to meet product needs by referring to the correlation matrix.', 'Based on the occurrence frequency of technological keywords, the keyword vector of each technology is generated.4.The fourth step identifies the configurations of existing technologies, matching keywords with the morphology
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			matrix.4.4.Module 3: mapping The final module completes the product- technology roadmap by combining the results from the preceding two modules:1.The first step is to link the two morphology matrices by analyzing the correlation between each level.']
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59	Determinants of Innovation Performance in Firms	['innovation', 'determinants', 'performance', 'equation', 'innovativeness', 'literature', 'organizational', 'measurements', 'firm', 'variables']	['the literature, various factors, referred to as the determinants of innovation, are shown to be related to the innovation level of firms.', 'In the majority of the existing innovation management literature, comprehensive research is absent; systematic investigation pertains only to relations between several of the innovation determinants and innovation performance.', 'In the majority of the existing innovation management literature, only the relations between a small set of the innovation determinants and innovation performance are investigated.']
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59	Business and Social Media Strategy Alignment	['media', 'social', 'organisations', 'strategies', 'alignment', 'business', 'extent', 'strategy', 'reports', 'organisation']	['Second, data for social media strategies were extracted from a single source - Twitter, which may yield an incomplete picture of the social media strategies and/ or orientations of the organisations.', 'studyThis research examines alignment between business and social media - specifically, the extent to which organisations achieve synergy between their business strategies and social media strategies is examined.', 'Whats your social media strategy?']
59	Association Rule Mining Algorithms	['association', 'rules', 'apriori', 'rule', 'confidence', 'predictive', 'algorithm', 'support', 'item', 'itemsets']	['In Table 1, association rules obtained by Apriori algorithm are presented.', 'In this study, three well-known aforementioned association rule mining algorithms, Apriori, Predictive Apriori and Tertius algorithms, were utilized in order to extract useful association rules on the data set.', 'In Table 2, association rules obtained by

			Predictive Apriori algorithm are presented.']
54	LDA-based Topic Modeling	['lda', 'topic', 'lsa', 'topics', 'model', 'document', 'blei', 'distribution', 'probabilistic', 'modeling']	['In the LDA topic model, the content of each topic is represented by a set of related words.', 'In the LDA topic model, the content of each topic is represented by some related words.', 'Therefore, researchers have developed various LDA-based time topic models based on LDA and time signals.']

54	TRIZ Inventive Principles in Sparse Innovation	['triz', 'inventive', 'principles', 'innovation', 'ma', 'design', 'sparse', 'engineer', 'altshuller', '40']	['The potential valuable opportunities were extracted based on the influence between TRIZ inventive principles and sparse innovation areas in the TRM.', 'According to the technology and product trends, we define new opportunities by the aid of TRIZ inventive principles.', 'The other one refers to the application of TRIZ inventive principles.']
51	SAO Structures & Technology	['sao', 'structures', 'saos', 'parser', 'structure', 'bulb', 'market', 'remained', 'battery', 'ao']	['It contains all of the SAO structures.', 'This research uses SAO structures.', 'Most of the SAO structures are phrases.']

48	Risk- Adaptive Technology Roadmap	['risk', 'adaptive', 'events', 'risks', 'plans', 'nodes', 'futuristic', 'roadmap', 'future', 'databases']	['After identifying possible risk events from futuristic databases, we explore necessary actions to achieve goals by responding to risk events in the future through monitoring occurrence of risk events, analyzing correlations between risk events and elements of TRMs, adapting strategies and changing paths, and establishing the new TRM concept.', 'The risk- adaptive roadmap is composed of four layers, technology, product , technology, and risk.', 'The risk-adaptive concept is to monitor and extract risk events from futuristic databases and then to provide plans for addressing the events .']
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48	Monitoring Roadmap Status & Impact of Key Driver Changes	['status', 'roadmap', 'changes', 'drivers', 'impact', 'key', 'ddrm', 'subdriver', 'signal', 'monitor']	['A signal is generated to inform the roadmapping team about the current roadmap status and provide an impact assessment of changes in key drivers.', 'These components automatically assess the impact of changes from key drivers of the current roadmap status with visualization to support decision-making.', 'status of a roadmap is determined on the basis of an impact assessment on changes in key drivers .Data']
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47	Genetic Algorithm in Chromosome Optimization	['chromosom e', 'chromosomes', 'fitness', 'mutation', 'local', 'genetic', 'gene', 'crossover', 'randomly', 'selected']	['The classification performance is used as the fitness function of each chromosome.', 'Update: If the fitness function score of the neighboring chromosome is better than the current chromosome, the current chromosome is updated accordingly, and local search for the modified chromosome is continued until no more improvement is attained.4.Genetic Operations: After the local search stage improves the current gene pool, genetic operations are conducted to develop the next generation.', 'For each chromosome, a local search is conducted to improve their fitness function scores.']
45	Software Development & Network Integration in Pandemic	['vol', 'softw', 'int', 'netw', 'iii', 'hum', 'ii', 'dÃ', 'civ', 'dev']	['Vol.', 'Vol.', 'Vol.']

44	RS-MultiBoosting in ML Forecasting	[rs', 'multiboosting', 'eml', 'bagging', 'method', 'diversity', 'methods', 'heml', 'iml', 'error']	[Second, the forecasting performance of RS-MultiBoosting method is compared with that of IML and EML.', 'In addition, many scholars suggest that the diversity of ML method can effectively improve the forecasting accuracy proposes a new HEML method, namely, the RS-MultiBoosting approach that is integrated by two widely used EML methods, i.e., the RS and MultiBoosting methods.', 'The RS-MultiBoosting method combine the advantages of RS with those of the MultiBoosting .']
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39	Foresight in Future Exercises and Methods	['foresight', 'futures', 'exercises', 'reflection', 'diamond', 'future', 'views', 'character', 'long', 'methods']	['Reports and foresight studies Foresight studies are a commonly used information source in foresight exercises.', 'An elaboration of the role of data in foresight shows that foresight only functions as a combination of qualitative and quantitative thinking.', 'Foresight support systems: The future role of ICT for foresight.']
38	AI Concept Categorizer Tool	['categorizer', 'concept', 'ai', 'facilitator', 'tool', 'list', 'group', 'categorization', 'negotiation', 'agent']	['The list of topics generated by the AI Concept Categorizer follows:A noticeable difference between the list generated by the expert□ facilitator and the AI Concept Categorizer is the difference in terms that comprise the clusters of each list item.', 'The AI Concept Categorizer supports this need.', 'AI Concept Categorizer.']

36	Data Lifecycle Roadmapping Challenges	['lifecycle', 'roadmapping', 'platforms', 'roadmap', 'pages', 'technologic', 'substantially', 'companies', 'does', 'mapping']	['However, since the early stages of the data lifecycle do not substantially affect product/service development, they were likely to be missed in the actual planning process.', 'However, this requirement makes it challenging for organizations to start such initiatives because they lack expertise in roadmapping.', 'However, the introduced data layers did not cover the data lifecycle, and data-related processes were overlooked in the respective technology layers .']
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10. APPENDIX 3: TOPIC FROM THE FIRST APPLICATION

Table 10 Topics extracted using BERTopic in AgeTech.

Topic Count	Topic Name
2765	2_Digital Healthcare and Patient Services
2234	3_Physical Activity & Wearable Technology
1695	5_Technology Adoption by Older Adults
1231	7_Robotic-assisted Cancer Surgery in Older Patients
1139	9_Pandemic Impact on Health and Society
956	13_Mild Cognitive Impairment & Dementia Detection
845	14_mHealth Smartphone Apps

824	15_Nutrition and Obesity Interventions
794	18_Social Robots in Healthcare & Interaction for Older Adults
794	19_Telehealth Services & Patient Satisfaction
653	23_Diabetes Management and Technology
514	26_Stroke Risk and Cardiovascular Treatment
487	27_Fall Prevention and Detection in Older Adults
431	28_Ehealth Literacy and Technology in Healthcare
340	29_Patient Inclusion in Hospital Studies

340	30_Influenza and COVID-19 Vaccination
311	31_Immersive Virtual Reality for Older Adults
308	33_Intervention Effectiveness & Feasibility
300	34_Chronic Pain Management
300	35_Frailty Assessment in Older Adults
297	36_Cost-Effectiveness and Quality-Adjusted Life Years
289	38_Dental Caries and Treatment
285	40_Cognitive-Game Based Training for Older Adults

281	41_Medication Management and Pharmacy Systems
280	42_Loneliness & Social Isolation
279	44_Smart Home Assisted Living for Elderly
270	45_Brazilian Health Collective Post-Graduation
264	47_Driving Cessation & Safety in Older Adults
258	48_Hearing Loss and Hearing Aid Usage
252	49_Sleep Quality and Actigraphy
240	51_Smoking Cessation and Support
240	52_Voice Assistants for Older Adults' Health
237	54_Blood Pressure Monitoring and Control

230	56_Hip Fracture Recovery
222	58_Video Telehealth for Older Adults and Veterans
213	60_Mobile Health Technology & Medication Adherence
195	62_Vision Impairment and Eye Health
157	65_MRI and CT Scans in Radiology

11. APPENDIX 4: TOPICS FROM THE SECOND APPLICATION

Response	Count
Social Robots for Elderly Care	3646
Assistive Technology for Older Adults	2821
IoT-Based Elderly Health Monitoring Systems	2044
Wearable Technology for Physical Activity in Older Adults	1812
Older Adults' Use of Digital Technology for Social Interaction	1522
Lithium-Ion Battery State of Health Estimation	1273
Elderly Fall Detection Using Machine Learning	895
Human Activity Recognition Using Sensors	867
Alzheimer's Disease Diagnosis Using Machine Learning	855
Telemedicine for Older Adults During COVID-19 Pandemic	786
Structural Health Monitoring for Bridges and Structures	619
Autism and Health-Related Technologies	512
Fall Risk Assessment in Older Adults	501
Aging and Health in Society	500
Home Care and Technology for Ageing	488
Artificial intelligence in Healthcare	458
eHealth Literacy in Older Adults	416
Machine Learning in Biological Aging	395
Immersive Virtual Reality for Older Adults	378

Telemedicine for Elderly Patients During COVID-19 Pandemic	340
Healthcare Expenditure and Resource Allocation	332
COVID-19 Impact on Older Adults' Mental Health	329
Mild Cognitive Impairment in Older Adults	324
Skin and Aortic Valve Health	317
Depressive Symptoms and Assistive Technology	305
Brain Age and Epigenetic Methylation	302
Wearable Health Monitoring Sensors	295
Smart Monitoring for Dementia and Alzheimer's Patients	283
Diabetes and Obesity Prediction Using Machine Learning	268
Emergency Virtual Reality and Digital Rehabilitation Technology	264
Chronic Disease Self-Management and Multimorbidity	261
Smart Elderly Care Services	255
Voice Assistants for Older Adults	250
Digital Health Adoption in Older Adults	247
Hearing Aid Use and Hearing Loss in Older Adults	237
Power Electronics Health Monitoring and Reliability	236
Conversational Agents for Dementia Care	231
Transformer Health Index and Insulation Assessment	225
Glaucoma and Nutrition in Older Adults	221
Heart Disease Prediction Using Machine Learning	217
Medication Adherence and Electronic Dispensing Systems	214

Robotic Exercise Assistance for Older Adults	205
Privacy Concerns in Video-Based AAL Technologies	204
Wireless Body Area Network Security and Authentication	204
Architectural Design and Heart Failure Risk Profiling	192
Air Pollution and Health Impacts	181
Emergency Department Critical Care	180
Digital Health Interventions for Cancer Patients	180
Passive Remote Monitoring for Home Care	175
Dementia Care and Assistive Technologies	173
ECG Monitoring and Wearable Heart Devices	169
mHealth Solutions for Diabetes Self-Management	167
Social Isolation and Loneliness in Older Adults	165
Chronic Disease Home-Based Care Practices	161
Design Guidance for Video Chat Systems	159

12. APPENDIX 5: PRISMA-P GUIDELINES

PRISMA-P (Preferred Reporting Items for Systematic review and Meta-Analysis Protocols)

2015 checklist: recommended items to address in a systematic review protocol*

Section and topic	Item	Checklist item
	No	
ADMINISTRATIVE INFORMATION		
Title:		
Identification	1a	Identify the report as a protocol of a systematic review
Update	1b	If the protocol is for an update of a previous systematic review, identify as such
Registration	2	If registered, provide the name of the registry (such as PROSPERO) and registration number
Authors:		
Contact	3a	Provide name, institutional affiliation, e-mail address of all protocol authors; provide physical mailing address of corresponding author
Contributions	3b	Describe contributions of protocol authors and identify the guarantor of the review
Amendments	4	If the protocol represents an amendment of a previously completed or published protocol, identify as such and list changes; otherwise, state plan for documenting important protocol amendments
Support:		
Sources	5a	Indicate sources of financial or other support for the review
Sponsor	5b	Provide name for the review funder and/or sponsor
Role of sponsor or funder	5c	Describe roles of funder(s), sponsor(s), and/or institution(s), if any, in developing the protocol
INTRODUCTION		

Rationale	6	Describe the rationale for the review in the context of what is already known
Objectives	7	Provide an explicit statement of the question(s) the review will address with reference to participants, interventions, comparators, and outcomes (PICO)
METHODS		
Eligibility criteria	8	Specify the study characteristics (such as PICO, study design, setting, time frame) and report characteristics (such as years considered, language, publication status) to be used as criteria for eligibility for the review
Information sources	9	Describe all intended information sources (such as electronic databases, contact with study authors, trial registers or other grey literature sources) with planned dates of coverage
Search strategy	10	Present draft of search strategy to be used for at least one electronic database, including planned limits, such that it could be repeated
Study records:		
Data management	11a	Describe the mechanism(s) that will be used to manage records and data throughout the review
Selection process	11b	State the process that will be used for selecting studies (such as two independent reviewers) through each phase of the review (that is, screening, eligibility and inclusion in meta-analysis)
Data collection process	11c	Describe planned method of extracting data from reports (such as piloting forms, done independently, in duplicate), any processes for obtaining and confirming data from investigators
Data items	12	List and define all variables for which data will be sought (such as PICO items, funding sources), any pre-planned data assumptions and simplifications

Outcomes and prioritization	13	List and define all outcomes for which data will be sought, including prioritization of main and additional outcomes, with rationale
Risk of bias in individual studies	14	Describe anticipated methods for assessing risk of bias of individual studies, including whether this will be done at the outcome or study level, or both; state how this information will be used in data synthesis
Data synthesis	15a	Describe criteria under which study data will be quantitatively synthesised
	15b	If data are appropriate for quantitative synthesis, describe planned summary measures, methods of handling data and methods of combining data from studies, including any planned exploration of consistency (such as I^2 , Kendall's τ)
	15c	Describe any proposed additional analyses (such as sensitivity or subgroup analyses, meta-regression)
	15d	If quantitative synthesis is not appropriate, describe the type of summary planned
Meta-bias(es)	16	Specify any planned assessment of meta-bias(es) (such as publication bias across studies, selective reporting within studies)
Confidence in cumulative evidence	17	Describe how the strength of the body of evidence will be assessed (such as GRADE)

*** It is strongly recommended that this checklist be read in conjunction with the PRISMA-P Explanation and Elaboration (cite when available) for important clarification on the items. Amendments to a review protocol should be tracked and dated. The copyright for PRISMA-P (including checklist) is held by the PRISMA-P Group and is distributed under a Creative Commons Attribution Licence 4.0.**

From: Shamseer L, Moher D, Clarke M, Ghersi D, Liberati A, Petticrew M, Shekelle P, Stewart L, PRISMA-P Group. Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015: elaboration and explanation. BMJ. 2015 Jan 2;349(jan02 1):g7647.

13. APPENDIX 6: EXCERPT OF AGETECH REPORT

This is a excerpt of the AgeTech report, the entire report can be found in GitHub (<https://github.com/DataGomes/ReportRAG>)

1. Social robots for elderly care

Social Robots for Elderly Care are being increasingly considered as a solution to address the challenges posed by the aging global population, which is expected to reach 2.1 billion people over 60 years old by 2050. These robots, known as Socially Assistive Robotics (SARs), aim to enhance the quality of life (QoL) for seniors by providing necessary assistance and alleviating the shortage of manpower in elderly care. Studies have shown that tailoring the characteristics of SARs to meet the specific needs of the elderly is crucial for their acceptability and effectiveness. Examples of such robots include Pepper and Nao, which have been proposed for different care scenarios. Research has also focused on optimizing the assignment of robots to elderly individuals to maximize efficiency and minimize caregiver stress, as seen in the ENRICHME project. This project emphasizes the importance of long-term interaction and monitoring to support the independence of older adults with mild cognitive impairment. Additionally, focus group discussions have highlighted the need for thorough planning, pre-training, and customization of robots to address user characteristics, functionality, and barriers to adoption. Social robots are also being developed to conduct cognitive stimulation sessions, either autonomously or in collaboration with therapists, to support active aging in both home and daycare settings.

References

- Robots for Elderly Care: Review, Multi-Criteria Optimization Model and Qualitative Case Study
- Employing Socially Assistive Robots in Elderly Care
- A social robot assisting in cognitive stimulation therapy

2. Assistive technology for older adults

Assistive Technology for Older Adults is increasingly important in our aging society, especially with the rise of information and communication technologies post-COVID-19. A comprehensive guide categorizes these technologies, summarizing evidence across various domains. Research

highlights a significant gap between the needs of older adults and their adoption of assistive technologies, identifying critical areas such as health, leisure, safety, communication, and social involvement. The most pressing needs include support for daily activities, mobility, smart kitchen technology, and maintaining social contacts. Assistive technologies range from simple devices to complex robotic systems, enhancing independence and quality of life for older adults. Despite their benefits, these technologies face challenges and limitations, which are crucial for ongoing research and development to address.

References

- Older People's Needs and Opportunities for Assistive Technologies
- A Complete Guide to Assistive Technology for the Elderly – At Least, by Now
- Discernment on assistive technology for the care and support requirements of older adults and differently-abled individuals