Futures 164 (2024) 103476

Contents lists available at ScienceDirect

Futures

journal homepage: www.elsevier.com/locate/futures

Technological Scanning for Foresight: The case of Metaverse applications for Healthcare

Francesca Zoccarato *, Antonio Ghezzi, Emanuele Lettieri, Giovanni Toletti

School of Management, Polytechnic University of Milan, School of Management, Milan, Italy

ARTICLE INFO

Keywords:
Foresight
Text mining
Scanning
Forces of change
Trends
Metaverse

ABSTRACT

The process of foresight, which allows companies and organizations to build scenarios and inform the creation and sustainment of their competitive advantage, relies on the integration of several steps. Scanning is a crucial step of foresight, as it informs and influences the results of the whole process and, thus, the strategic decision-making of the company. Sources and methods of scanning for foresight analysis can be diverse and lead to different results, although few studies investigate such differences: more specifically, the informative power of academic and non-academic articles and reports has not been assessed yet. This study aims to shed novel light on how the different analysis methods of full reading of records and text mining analysis isolate and gather forces of change differently, based on the source analyzed. The study's empirical context is the metaverse and its application in healthcare. We find that each source and method by itself is unable to fully gather the whole set of forces of change; however, each source presents some topics that are specific to the target readers of the source, and each methodology presents some advantages as well as some limitations. From the comparison of the results, theoretical and managerial implications are drawn.

1. Introduction

Today's complex and dynamic business environments pose several challenges to firms and policymakers, which have to respond quickly to events such as technological advancement, emerging market players, disruptive political events, pandemics, and economic downturns (Zhang-Zhang et al., 2022). Foresight has been developed to address such challenges, which is *the application of systemic, participatory, future-intelligence-gathering, and medium to long-term vision-building process to informing present-day decisions and mobilizing joint actions* (Saritas et al., 2022). In this process, the scanning phase of signals of change is a very relevant and recurrent step, which allows the timely detection of changes in the environment (Marinković et al., 2022). However, one crucial challenge is data gathering. Indeed, most of the methods utilized in foresight rely on either participatory methods with experts' opinions or desk research, such as literature analysis (Marinković et al., 2022). As the volume of data from heterogeneous sources has considerably grown, identifying the relevant data from the huge quantity of available information is challenging and more effort and time are needed in monitoring thematic fields, and traditional methods might show their limitations (Kayser & Blind, 2017). Additionally, the process has been accused of being too qualitative (Hirsch et al., 2019), not integrating qualitative and quantitative methodologies, and missing opportunities from the huge value of big data, although this holds the potential to improve foresight with new quantitative tools (Kayser

* Corresponding author.
E-mail addresses: francesca.zoccarato@polimi.it (F. Zoccarato), antonio1.ghezzi@polimi.it (A. Ghezzi), emanuele.lettieri@polimi.it (E. Lettieri), giovanni.toletti@polimi.it (G. Toletti).

https://doi.org/10.1016/j.futures.2024.103476
Received 6 February 2024; Received in revised form 22 July 2024; Accepted 11 September 2024
Available online 18 September 2024
0016-3287/

& Blind, 2017). Indeed, recent studies have tried to exploit text mining approaches to social media or web data (Kayser & Blind, 2017; Kayser & Shala, 2020; Zeng, 2018) to assess the potential of such methods and data sources to improve scanning methods and better exploit quantitative data. However, the results of these methods have never been compared to the ones of more traditional methods to understand if they offer higher opportunities to gather forces of change. Therefore, the aim of this study is to compare the results obtained from different methodologies and diverse data sources. More specifically, we compare academic articles, non-academic articles, and reports with diverse methods of analysis, such as text mining and extensive reading, namely the traditional accurate reading of the records. Such analyses are applied as an example to an emerging topic, namely the future of Metaverse applications in healthcare. Therefore, the article begins with the introduction of the topic, continues with the introduction of the methodology used, and eventually the results are discussed, and then final conclusions are drawn.

2. Literature review

2.1. Foresight

The field of foresight has evolved from its inception to better inform public policy and assist corporations as well as specific conventional institutions in decision-making processes and strategic thinking (Ko & Yang, 2024). This approach strongly relies on the integration of diverse methodologies and data, and based on the objectives and application levels, different tools can be selected and combined (Martin, 1995). Diverse results are enabled by the selection of different methods, and nevertheless, few investigations have been carried out about how methods can inform the foresight process (Popper, 2008). More specifically, the scanning phase in foresight is intended as the search for any signal of change (Hines, 2020) and is a key step to getting an overview of the present situation (Marinković et al., 2022). This initial phase has garned strong attention in past studies (Flick et al., 2020; Hakmaoui et al., 2022) as it informs and influences the following steps of the process, thus allowing the generation of diverse strategies (Idoko & MacKay, 2021; Lehr et al., 2017; Maresch & Gartner, 2020; Rohrbeck & Kum, 2018).

The scanning phase can vary both in terms of the sources from which data are extracted and in terms of the analysis through which the forces of change are identified. While experts' opinions are widely adopted (Amorim-Lopes et al., 2021; Darkow, 2015; Inkinen et al., 2021; Lehr et al., 2017; Marinković et al., 2022), experts' biases represent a relevant issue in effectively identifying emerging opportunities and threats, and are therefore often integrated with other data sources, as academic articles and grey literature in the form of non-academic article and reports (Apreda et al., 2019; Marinković et al., 2022). These additional sources of data are relevant, although underexploited, as more recent methodologies, such as text mining, can exploit them to better inform experts and help them to partially overcome their bias (Bonaccorsi et al., 2020; Kayser & Blind, 2017).

Academic articles have been exploited in foresight processes (Darkow, 2015; Kim et al., 2021) as they disseminate the latest developments of different technologies (Behkami & U. Daim, 2012; Li, Xie, Daim, et al., 2019). Both institutional and non-institutional reports are exploited in foresight processes, in the forms of governmental plans such as the ones produced by various institutions such as OECD, United Nations, World Economic Forum, as well as market reports of consultancy companies and industry associations (Boe-Lillegraven & Monterde, 2015; Darkow, 2015; Metz & Hartley, 2020). Grey literature applied to foresight encompasses also non-academic articles as, but not limited to, industry news accounts (Rohrbeck et al., 2015) and industry publications (Apreda et al., 2019).

These sources can be analyzed in different ways, for instance through the reading of the record by the researcher or more generally by actors involved in the foresight processes (Costa Climent & Haftor, 2021; Heger & Rohrbeck, 2012; Metz & Hartley, 2020) or through the application of methodologies such as text mining techniques. Text mining is an increasingly implemented method to access technical and non-technical information from diverse sources, such as patent documents (Madani & Weber, 2016), academic articles (De Miranda Santo et al., 2006), social networks (Li, Xie, Jiang, et al., 2019) and general web sources (Kayser & Shala, 2020). Text mining can exploit a wide number of methods, from the retrieval of the most frequent n-grams (Blei et al., 2003) to more complex topic modeling algorithms such as the Latent Dirichlet Allocation (LDA) which allows detecting latent topics in the analyzed text (Blei, 2012; Kayser & Shala, 2020). The different combinations of the sources with the analyses can lead to different results, and this will be therefore investigated in a research area that is full of promising areas of development: the metaverse and its application in healthcare.

2.2. Metaverse and Healthcare applications

The term 'metaverse' was first coined in 1992 by author Neal Stephenson in his book named Snow Crash, who described a virtual world where humans could interact through their avatars. From this very first naming, the paradigm of the metaverse has evolved, still, the three-dimensional virtual world can be described as a place where users can live as avatars, interacting with others for work and fun, experiencing an alternative life (Wang et al., 2022). This creates an environment through a metaphor of the real world, without its physical limitations (Davis et al., 2009).

The Metaverse is accessible using Extended Reality (XR), and is based on a set of emerging technologies such as Virtual Reality (VR), Augmented Reality (AR) and Mixed Reality (MR), 5 G, wearable sensors, AI, non-fungible token (NFT) and blockchain (Ali et al., 2023; Chin et al., 2022; Lee et al., 2021). The growing maturity of these technologies enables the metaverse to move from an early stage toward a more established stage (Plechatá et al., 2022; Wang et al., 2022). The metaverse will be developed and exploited by a diverse set of actors with varying degrees of interdependency. Similar to other digital platforms and solutions, the metaverse may represent an opportunity to contribute to the rapid transformation of healthcare, by providing relevant benefits such as building new business models for the co-creation of goods and services, enabling wider patients to reach cares, access new capabilities, and finally increase business performances (Schiavone et al., 2021). Indeed, the metaverse in Health and Fitness has been valued US$6.57bn in 2023, with a compounded annual growth rate (CAGR 2023–2030) of 35.28 %, resulting in a projected market volume of US$54.47bn by 2030 (Statista, 2023). Alongside the business opportunities, the metaverse enables the possibility of accessing a series of services from the comfort of home, without geographical limitations, opening new channels of treatment, wellness and fitness at lower costs while improving patient outcomes. Additionally, the interactions with doctor avatars in the metaverse compared to more traditional automatic medical chatbots or VR yields several differences, for instance, it allows patients to create a more empathetic and therefore more effective relationship with the doctor (Sestino & D'Angelo, 2023). These experiences include and are not limited to meeting the therapist as a digital avatar, sharing more easily the digital medical data collected from their direct-to-consumer wearables, meeting fellow patient communities to share the treatment progress, foreseeing the negative long-term consequences of unhealthy behaviors, or experiencing the world by different perspectives such as one of the vulnerable individuals (Plechatá et al., 2022). These experiences could yield several benefits in terms of patients' path of care, yet several challenges exist. These are related not only to data attacks (Ruiz Mejia & Rawat, 2022), but also to the interoperability among metaverse architectures and the ones of electronic health systems and unequal access to care due to the economic affordability of devices to access the metaverse. Such a field with its rapidly changing conditions is a fruitful ground to test how diverse methodologies can gather different forces of change in terms of the width of records and deepness of discussion, generating interesting insight into future business and technology development.

3. Methodology

In this study, we exploit a combination of data sources and analyses to provide an overview of the forefront applications of the metaverse in healthcare and understand whether diverse approaches lead to different results in the scanning phases. The analyses have been carried out on academic articles, non-academic articles and industry and consulting firms reports through two different methodologies, namely through their extensive reading and text mining approaches.

3.1. Data collection

Two different search strategies have been exploited to gather the records and results of the searches are reported in Table 1. It is relevant to note that the main objective of this search is not to look for all the results about Metaverse and the future of Health, rather to find relevant contributions upon which the different methodologies could be run and that could bear insights about the different types of information highlighted by each source.

First, we combined the reference technology (Metaverse) with the sector under consideration (Healthcare). Second, we selected keywords pertaining to the future of the healthcare system. This was done to determine whether the future needs of the healthcare sector were compatible with the opportunities and possibilities that the metaverse can offer. Both queries were run in June 2022 for the three types of sources, namely academic articles, non-academic articles, and foresight reports, with some minor modifications so that each query could be adapted to the search engine.

For the first strategy, *Metaverse AND Health** were used for researching academic articles via Scopus by Elsevier over the last three years, as the most recent applications were deemed to be of the utmost importance to scan relevant drivers. The analysis returned 36 papers, while *Metaverse and Healthcare* were used to search for grey literature as reports and non-academic articles in Google and Google Scholar and returned 13 non-academic articles and 9 reports, by looking at the first three pages of both Google and Google Scholar and selecting the relevant records, by assessing how thorough the records were and how much they were dealing with the topic of reference.

For the second strategy, *Healthcare AND Future AND Trend* were used for researching academic articles in Scopus. As the most recent applications were deemed to be of the utmost importance to scan relevant drivers, a time frame of three years was considered. Additionally, the most relevant subject areas were included, such as Medicine, Nursing, Health Professions, Computer Science, Social Sciences, Business, Management and Accounting, Decision Sciences, Economics, and Finance. From all potential categories of papers, only English- language books, articles, reviews, book chapters, and conference papers were chosen. It resulted in 511 papers. *Future AND Trends of healthcare* was instead the query used to search for grey literature as reports and non-academic articles in Google and Google Scholar. Again, in the first three pages of both browsers and the relevant, thorough and appropriate records were selected. This search resulted in 15 papers and 3 consulting firm reports.

Table 1
Queries and sources used for data collection.

	Sources			Total
	Academic Articles	*Non-academic articles*	*Report*	
Query	Scopus	Google, Google Scholar	Google	
Metaverse in healthcare	36	12	9	57
Future of healthcare	511	15	3	529
Total	547	27	12	586

3.2. Data analysis

Extracted data were analyzed in two different ways, which are commonly used in the foresight process, namely extensive reading and text mining.

3.2.1. Extensive reading

The first method implemented is the researcher's reading of the identified documents. For what concerns the academic literature, the number was narrowed down by a first abstract and title screening. Indeed, from this step, some papers turned out to not be about the future development of healthcare or about the future of metaverse, therefore, 10 articles from the first query and 24 records form the second query were analyzed. This led to reading an overall number of 74 records, as shown in Table 2.

Records from each of the three sources were read, the forces of change were extracted through a process of coding, and an additional set of information was elaborated for each force of change. Specifically, a name was given to each force of change, keeping track of what were the related search strategy and the source. Each force of change was also classified into possible types of forces of change. In this case, four labels could be assigned according to the classification proposed by Saritas and Smith (2011). **Driving forces (or drivers)** are factors and uncertainties, relevant and distinct, that create or drive change within one's business or institutional environment. **Trends** are the underlying patterns of change that have a relatively clear direction of change. **Uncertainties** are emerging issues that are happening, but we cannot agree on how they would evolve and in which direction. **Weak signals** are less advanced, noisy, or socially situated indicators of change in trends and systems; they constitute raw informational material for enabling anticipatory action. Additionally, each force of change was classified through the *Scanning template*. Specifically, we relied on the categorizations of the scanning template of Van Wyk (1997), which in turn strongly relies on the "landscape evolution model" developed by Higgs (1990). The model encompasses seven categories, namely, nature, institutions, demography, politics, society, economy, and technology. Additionally, we analyzed the level of detail of the information related to the force of change. We have tagged with "1" the forces of change that were mentioned but not discussed in depth, "2" when they were addressed with a moderate level of detail but without providing information or technical details, and "3" whenever in addition to mentioning the force of change in question, technical details, and contextualization of the force of change in question were provided. Eventually, the overall number of forces of change gathered by each source was computed.

3.2.2. Text mining

Text mining is a technique that allows, by using natural language processing software, to analyze large amounts of unstructured textual data to identify key topics, keywords, and other useful attributes (Fan et al., 2006). Therefore, text mining demonstrates its value by converting this volume of documents into an analyzable and structured list of keywords that is easier to handle compared to unstructured text (Kwon et al., 2017). Thanks to the vast number of documents that text mining enables rapid analysis of, it is possible to avoid biases resulting from the selection of experts as well as biases in the experts' opinions (Kayser & Shala, 2020). Text mining commonly follows four steps (Kayser & Blind, 2017; Li et al., 2015), namely data source selection, text pre-processing, data analysis and data interpretation. Accordingly, the first step is the selection of data sources according to the research question from a wide variety such as academic literature, social media, institutional or consulting firms reports, and third-party databases. Afterward, documents need to be transformed into machine-readable text. Therefore, documents are "tokenized" into individual lists of words. Tokenized documents are then cleaned from "stopwords" (articles, conjunctions, pronouns) and other irrelevant terms as well as punctuation. Next, "lemmatization" (which reduces words to the root form based on a dictionary) may be applied to simplify the analysis and better capture relevant terms. Eventually, the software that counts the most frequent words or n-grams (contiguous sequences of n words) and topic modeling algorithms are applied to tokenized documents to extract information. Since information extracted in this step cannot be self-explanatory, as the last step of the process, results need to be interpreted to avoid biases and representability limitations (Kayser & Blind, 2017; Kayser & Shala, 2020). One critical aspect is related to the concept of the "topic modeling algorithm". Topic modeling algorithms are statistical methods that allow examining textual sources to identify recurring themes inside them. A theme is considered as a collection of strictly related words, formally known as "topics", as formally, a topic can be defined as "a distribution over a fixed vocabulary" (Blei, 2012). The main assumption in this model is that documents are generated by a combination of several recurring topics; each term composing a topic has a certain probability of belonging to that topic (and to others too) and each topic has a certain probability of belonging to a given document. Therefore, each topic is made up of a number of words (with their relative probabilities) and each document is made up of a number of topics (with their relative probabilities). As it is argued by Blei (2012), since it is assumed that documents are "generated" by a set of topics, textual data can be considered as the result of a generative process that includes observed variables (the words which compose a document) and hidden variables too (topic structures). Overall, LDA defines a joint probability distribution over both types of variables which describes the dependencies on topic

Table 2
Documents analyzed through the extensive reading.

Query Keyword	Sources			Total
	Academic Articles	*Non-academic articles*	*Report*	
Metaverse in healthcare	10	12	9	32
Future of healthcare	24	15	3	42
Total	34	27	12	74

assignments and the words involved. To run a text mining analysis, we generated a text mining algorithm that was applied to all six clusters of textual sources separately, on the records shown in Table 3.

To generate the code, we relied on Matlab (R2020b) and its dedicated text analytics toolbox. The code included procedures for the second and third phases of text mining, such as the pre-processing of textual data, the portraying a list of the most frequent terms, the portraying a list of the most frequent bigrams (n-grams where $n = 2$) and eventually, extracting the most relevant topics out of the documents that compose each cluster through a topic modeling algorithm named "Latent Dirichlet Allocation" (Blei et al., 2003).

As a last phase, following the process of Kayser and Shala (2020), the top ten most relevant terms of each topic were interpreted to assign a meaning to the topic, and each topic was thus labeled. By doing this process, any topic that could represent a force of change has been added to the list, otherwise, it was discarded.

3.2.3. Source and method comparison

As a last step of the analysis, we compared how the different sources and methodologies performed in gathering signals of change. First, we compared the forces of change gathered by each source, then, we compared the forces of change gathered by each methodology. The final list of forces of change gathered by each source and by each methodology has undergone a multiple data cleaning process, where the authors gave to each topic a name, eliminating all the duplicates but ensuring to be comprehensive of all the forces of change, to be sure that those forces of change, differently named, gathered by multiple sources, where actually included. When some disagreements arose, the authors discussed to reach an agreement. The graphical representation of such analysis has been through Venn diagrams.

4. Results

4.1. Results of extensive source reading

Through the extensive reading of the 74 sources shown in Table 1, 475 forces of change were collected. The 475 forces were analyzed and coded, and similar forces of change were clustered in the same topic, thus the final number of topics dealt with is 62. However, as the aim of the analyses includes, for instance, the investigation of how in-depth each record is presented or how many records per paper are presented, it was necessary to maintain the full list also with duplicates for the analysis.

The forces of change were clustered with respect to the scanning template, as reported in Table 4. It is shown that the vast majority of the forces were related to the technological side (80 %), followed by the social side (14 %), natural (2 %) and economical (2 %) dimensions, institutional (1 %), and political (0,5 %) and demographical (0,5 %). Additionally, most of the gathered forces of change have been classified as trends (68 %), followed by uncertainties (19 %), driving forces (11 %) and eventually weak signals (3 %).

The average level of detail has always been medium-high, as shown in Table 5, with an overall average of 2,43, with natural and social dimensions being majorly discussed (av. 2,7 and 2,6 respectively), as well as economical (2,5) and technological (2,41), and the remaining dimensions with an average of around 2.

Afterwards, we analyzed the differences between the different sources in terms of forces of change gathered per source, and the results are presented in Table 6.

The academic articles are the ones that provided the most forces of change, followed by grey literature articles and finally reports. This is majorly due to the fact that relevant reports are scant, and more time and money are required to collect them with respect to other sources. However, reports are the ones that provide the highest number of forces of change per document on average, as they often provide a deep overview of the market or technology of reference. For what concerns the level of detail with which the different forces of change are treated, academic papers and reports show a significantly higher level of detail than non-academic articles. This is due to the fact that grey literature frequently deals with business-related elements of technologies without going into further details. Academic articles also demonstrate a remarkable capacity for treating forces of change in considerable depth, as they frequently employ experiments to evaluate forces of change by presenting data derived from real-world experience.

While the comparison of the distribution of the forces of change among the dimensions of the scanning template did not show any relevant difference, it is of interest to investigate classification of the forces of change, as shown in Table 7.

It is shown how non-academic articles have a higher potentiality in spotting trends, indeed they are the easiest to gather and therefore they can be easily discussed in grey literature. Instead, non-academic articles are not performing well in spotting uncertainties, as they probably represent the least interesting topic with respect to weak signal or trends as in most cases uncertainties are emerging topics with blurred boundaries.

Table 3
documents analyzed through text mining.

Query Keyword	Sources			Total
	Academic Articles	*Non-academic articles*	*Report*	
Metaverse in healthcare	10	12	9	32
Future of healthcare	24	15	3	42
Total	34	27	12	74

Table 4
Classification of the forces of change in the Scanning template.

Scanning template	Number of forces of change	% on the overall forces
Technological dimension	381	80 %
Social dimension	66	14 %
Natural dimension	10	2 %
Economical dimension	10	2 %
Institutional dimension	4	1 %
Political dimension	2	0,5 %
Demographical dimension	2	0,5 %
Total	475	-

Table 5
Average level of detail per force of change presented.

Dimensions	Demographical	Economical	Institutional	Natural	Political	Social	Technological	Overall
Av. level	2	2,5	2	2,7	2	2,6	2,41	2,43

Table 6
Forces of change per source.

	Number of forces of change	Av. number of force of change per sources	Average of Level of detail	Standard deviation of Level of detail
Non-academic articles	144	6	1,35	0,49
Academic articles	207	7	2,88	0,32
Report	124	12	2,95	0,22
Total	475		-	-

Table 7
Classification of the forces of change.

Source	Driving forces	% of driving forces	Trends	% of trends	Uncertainties	% uncertainties	Weak signals	% WS	Total
Non-academic articles	18	13 %	108	75 %	15	10 %	3	2 %	144
Academic articles	23	11 %	130	63 %	48	23 %	6	3 %	207
Report	9	7 %	84	68 %	26	21 %	5	4 %	124
Total	50		322		89		14		475

4.2. Text mining analysis

4.2.1. Academic articles

The first analysis conducted on academic articles is the Bigram analysis, which seeks to identify the most frequently occurring terms in the dataset of academic articles, and the results are shown in Table 8.

These results were further integrated with Latent Dirichlet Allocation (LDA), where topics are extracted in the form of collections of related words. We read and interpreted the top ten most relevant terms of each topic to understand what their underlying meaning could be; then, a name was assigned to each collection of words (topics) found by the algorithm. The clustering results are reported in Table 9.

The first, third, and ninth topics are all related to the macro area of education and learning in digital environments, which will be highly impacted by emerging technologies (Zou et al., 2020). For instance, educational activities for medical education through simulation allow for gaining and assessing competencies (Herrera-Aliaga & Estrada, 2022). In the ninth topic, the role of VR is discussed more in-depth with respect to other technologies such as blockchains. Indeed, such virtual realities allow medical students to access a comprehensive view of the human body as well as simulate new surgical techniques without risks (Chen & Zhang, 2022; Thomason, 2021). Similarly, as in the fourth topic, in virtual realities, therapies can be delivered, as in the case of an evidence-based intervention for ADHD patients (Zhang et al., 2022). Other topics encompass the key role of networks to share data and the thigh link with other technologies such as the blockchain (Jan et al., 2021). From the research on metaverse, topics more related to the VR experience emerge, both in broad terms as in topics six and eight, where both *physical* and *virtual* realities converge on an online space (Mozumder et al., 2022). This topic is revealed also by the bigram analysis, with the terms “virtual world” and “virtual reality”. This online environment can even become a platform for new applications and services (Wang et al., 2022), specifically in the field of care.

In the seventh topic, the role of the metaverse in the field of healthcare is studied. Patients can autonomously collect data through

Table 8
Most frequent bigrams in academic articles.

Force of change	Count	Related research query
internet of things	112	Healthcare AND Future AND Trend
blockchain technology	69	Healthcare AND Future AND Trend
autism spectrum	64	Healthcare AND Future AND Trend
smart devices	46	Healthcare AND Future AND Trend
wearable sensors	38	Healthcare AND Future AND Trend
regenerative medicine	38	Healthcare AND Future AND Trend
VR aided therapies	36	Healthcare AND Future AND Trend
security & privacy	35	Healthcare AND Future AND Trend
energy consumption	34	Healthcare AND Future AND Trend
machine learning	28	Healthcare AND Future AND Trend
emotion recognition	28	Healthcare AND Future AND Trend
wireless communication	27	Healthcare AND Future AND Trend
patient registries	27	Healthcare AND Future AND Trend
remote health	25	Healthcare AND Future AND Trend
sensor network	24	Healthcare AND Future AND Trend
health and metaverse	171	Metaverse AND Health*
diagnosis treatment	36	Metaverse AND Health*
metaverse medicine	33	Metaverse AND Health*
cybertherapy telemedicine	32	Metaverse AND Health*
immersive experience	26	Metaverse AND Health*
patient data	16	Metaverse AND Health*
virtual reality	643	Both
virtual world	151	Both
artificial intelligence	112	Both
augmented reality	78	Both
mental health	63	Both
medical education	56	Both
digital health	198	Both

Table 9
LDA results on academic articles.

Topics	Words	Related research query
1- Education in healthcare through simulation	medical, simulation, student, education, practice, visit, journal, nurse, clinical, skill	Healthcare AND Future AND Trend
2 - Network and application	application, user, challenge, network, access, various, layer, compute, exist, enable	
3 - Learning through virtual reality	virtual, reality, survey, learn, learning, improve, environment, result, training, tool	
4 - Virtual reality therapies	therapy, virtual, reality, crossref, exposure, health, nursing, disorder, anxiety, research	
5 - Blockchain and data	blockchain, device, datum, security, privacy, smart, internet, ieee, iomt, trust	
6 - Virtual world and its wide applications	virtual, world, application, reality, care, platform, education, digital, system, physical	Metaverse AND Health*
7 – Metaverse opportunities	metaverse, health, medical, patient, technology, research, data, healthcare, service, information	
8 - Virtual experience for patients	virtual, experience, environment, reality, technology, different, include, immersive, user, social	
9 - Metaverse for training	result, training, emotion, study, high, game, tool, change, treatment, university	

Table 10
Most frequent bigrams in reports.

Force of change	Related research query
digital health	Future and trends of healthcare
international cooperation	Future and trends of healthcare
digital transformation	Future and trends of healthcare
mental health	Future and trends of healthcare
patient experience	Future and trends of healthcare
virtual world	Metaverse and Healthcare
programmable world	Metaverse and Healthcare
digital twins	Metaverse and Healthcare
digital world	Metaverse and Healthcare
virtual assets	Metaverse and Healthcare
artificial intelligence	Metaverse and Healthcare
quantum computing	Metaverse and Healthcare
metaverse experience	Metaverse and Healthcare

body sensors, share them with their physicians and get information from them. The topic can encompass even some bigrams, such as "metaverse medicine" and "medical information". The quantity of bigrams pointing to the field of mental health is relevant, including also "emotion regulation". Indeed, the metaverse is likely to enhance the opportunities that VR already offers in this field. It is the case of cognitive behavioral therapy delivered through VR, for stress and pain management, and EndeavorRx is a relevant example being one of the first to prove not only its efficacy but being available only through prescription (Pandian et al., 2021).

4.2.2. Reports

The procedure applied to reports has been the same applied to academic articles, and both the most frequent bigrams and topics were retrieved, as shown in Tables 10 and 11.

In this case, topics are dealt with at a different level of specificity. For instance, topic 1 introduce generally the field of healthcare, as a complex system for delivering care and with a higher focus on the digital elements, although there are still relevant challenges for accessing these care services (KPMG, 2020). Some bigrams can support this topic, such as digital transformation and digital health. Whereas topic 4 introduces metaverse as an overview of such application, which can be a platform for patients' experience. Being industry-driven records, the topic of investment in healthcare plays a crucial role, indeed keywords related to this sphere such as equity, investment, capital and value and bigrams such as "virtual assets" emerge in these records. Similarly, the technological aspect related to the metaverse specifically emerges in the third topic, and with bigrams such as quantum computing and digital twins, as industry reports are more interested in the specific technologies enabling the metaverse application in healthcare and the related markets.

4.2.3. Non-academic articles

Both bigrams frequency analysis and LDA analysis were run on non-academic articles, and results are reported in the Tables 12 and 13.

In this case, some topics are quite in common with the previous sources. For instance, in topic 1, healthcare is presented in general as in topic 1 of reports, although keywords are more related to social and regulatory aspects such as policy, access, and costs. Similarly, topic 6 introduces the metaverse as a venue for changing and improving the experience of patients, as in topic 8 from academic articles, while topic 7 is referred to the application of the metaverse in healthcare, for instance for the medical education in surgery, as in topic 9 from academic articles. In this case, there are more topics related to technological innovation with respect to other sources, as in topic 2, and the topic of data emerges in topic 3 as well in topic 5 from academic articles. Topic 4 deals with the digitization of healthcare, for instance with the possibility of creating digital twins of patients for delivering treatments, which is a more specific application of technologies in the healthcare field. This topic is supported by bigrams such as digital twins and digital health. Topic 5 is related to general aspects of virtual reality topic, with the related bigrams of virtual reality and augmented reality, while in topic 8 metaverse is dealt with as an industry, with its possibilities of growth in the market size.

The analysis revealed that a significant proportion (67 %) of the forces of change identified through text mining pertained to the technological domain, with the remaining 27 % attributed to the social domain. However, text mining primarily provides keywords or phrases related to topics without sufficient contextual depth to cluster them into specific types such as trends, uncertainties, weak signals, or driving forces. This limitation arises because text mining relies on frequency-based analysis, focusing on well-established and frequently occurring themes within the data corpus. Consequently, while text mining effectively captures prevalent trends, it faces challenges in identifying weak signals—incipient changes with potential future significance in foresight studies.

4.3. Source and method comparison

As a last step of the analysis, the comparison of the forces of change gathered by each source is shown in Fig. 1, while the comparison of the forces of change gathered by each methodology is shown in Fig. 2.

The majority of forces of change are scanned through academic papers, although at the interconnection of at least two sources there are very relevant topics such as telemedicine, 5 G, wearables, Blockchain, Patient data. However, each source presents some topics that are specific to the domain. For instance, industry reports are very focused on those topics driving the industry and dealing with investment venues, such as patient experience and energy supply, governance, and drivers which will affect lots of industries working also on the boundaries of the field of healthcare. On the other side, non-academic records span in multiple directions, for instance, by introducing new and emerging topics, and academic records are able to go in depth to one main topic and to the most related ones. Indeed, these very specific topic per each source are the ones that are not in the combined areas. Academic records typically deal with the technological dimensions, while reports and non-academic articles explore also social, economic, political and institutional

Table 11
LDA results from the reports.

Topics	Words	Related research query
1 - Healthcare	health, care, healthcare, system, service, digital, international, clinical, change, deliver	Future and trends of healthcare
2 - Investments in healthcare	deal, healthcare, billion, private, equity, provider, investment, global, value, capital	
3 - Metaverse and computational aspects	world, compute, technology, digital, programmable, unreal, data, impossible, business, webme	Metaverse and Healthcare
4 - Metaverse in general	metaverse, virtual, world, real, platform, technology, include, social, system, network	

Table 12
Most frequent bigrams in non-academic papers.

Force of change	Related research query
digital health	Future and trends of healthcare
wearable device	Future and trends of healthcare
patient data	Future and trends of healthcare
cloud computing	Future and trends of healthcare
virtual worlds	Metaverse and Healthcare
digital twins	Metaverse and Healthcare
mental health	Metaverse and Healthcare
education and training	Metaverse and Healthcare
virtual reality	Both
augmented reality	Both
artificial intelligence	Both

Table 13
LDA analysis results on non-academic papers.

Topics	Words	Related research query
1 - Healthcare systems	care, health, system, provider, policy, population, access, information, cost, market	Future and trends of healthcare
2 - Technological innovation	health, digital, industry, device, challenge, virtual, reality, innovation, people, telehealth	
3 - Data for healthcare	healthcare, technology, patient, data, trend, help, improve, treatment, wearable, share	
4 - Digital healthcare	healthcare, patient, health, digital, potential, technology, medical, twin, mental, people	Metaverse and Healthcare
5 - Virtual reality	virtual, reality, data, technology, environment, platform, headset, even, case, process	
6 - Metaverse and users	metaverse, user, application, work, physical, share, bring, social, change, collaboration	
7 - Metaverse applications	surgery, room, medical, surgeon, education, operating, training, hospital, learn, student	
8 - Metaverse as an industry	metaverse, healthcare, market, industry, several, growth, information, expect, segment	

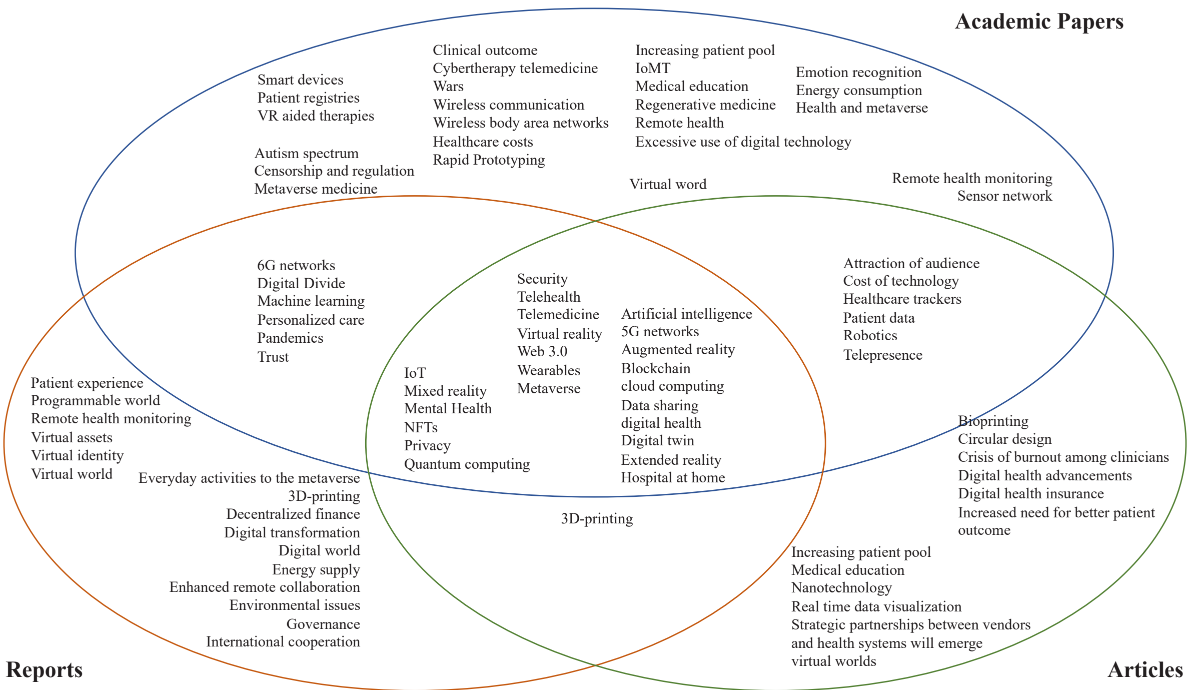

Fig. 1. Source comparison.

dimensions. Additionally, reports are more comprehensive and show more forces of change per document, showing examples and thus providing a clearer picture of the field.

The majority of forces of change are not at the interconnection of at least two methodologies, but each methodology gathers some specific forces of change. Extensive reading not only provides a wide set of records, but each information is contextualized with a set of additional elements that might indicate to other forces of change. On the contrary, text mining is able to provide a wide set of words and their allocation in topic, without pinpointing the exact theme of reference.

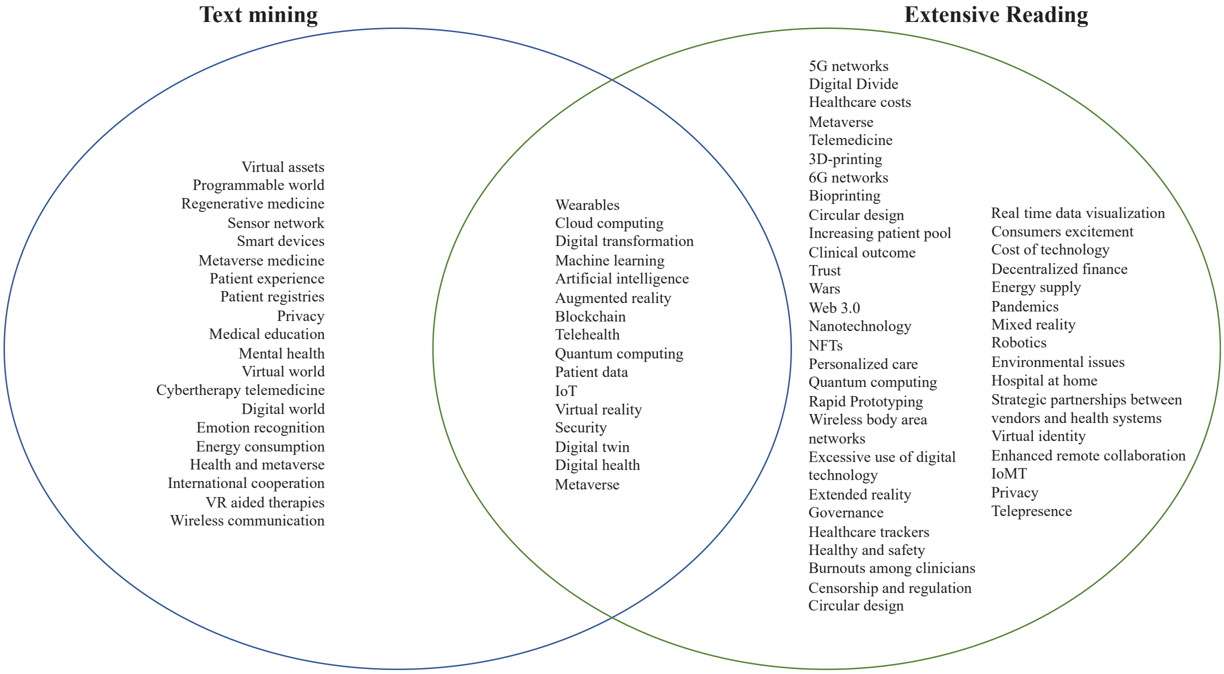

Fig. 2. Methodology comparison.

5. Discussion

The primary objective of this article is to understand the different informational potentialities and properties that various sources and methods offer to the foresight process, particularly during the scanning phase (Popper, 2015). This phase is crucial for the entire foresight process as the forces of change identified can significantly influence subsequent steps and the scenarios developed (Marinković et al., 2022), which, in turn, are fed into the strategic decision making of organizations.

To achieve our objective, a scanning analysis was conducted on the emerging topic of the future of the metaverse in healthcare. Three types of sources were analyzed: (i) academic articles, (ii) non-academic articles, and (iii) reports from industry and consultancy firms. These sources were examined using two alternative methodologies: extensive reading and text mining.

From a theoretical standpoint, several key insights emerge from our study. Regarding scanning sources, the literature on foresight has often overlooked the importance of selecting appropriate sources and methods for gathering information. Typically, studies select sources without a specific rationale, assuming that all sources and methods are equally effective. Our findings challenge this assumption by demonstrating that different sources yield varying results, particularly in terms of the scanning template and contextualization. Consequently, the choice of sources should be carefully tailored to the specific objectives of the foresight exercise and the scanning phase.

Additionally, concerning scanning methods, there is a prevalent assumption that quantitative methodologies and big data can vastly improve scanning efficiency by processing large volumes of information quickly (Kayser & Blind, 2017). However, our results indicate that text mining methodologies, which rely on frequency analysis, may miss significant emerging changes, such as, in this example, the development of 5 G technology as an enabler for metaverse in healthcare. These methodologies struggle to identify weak signals, which, however, are critical in foresight. In contrast, extensive reading allows for the detection of single mentions of significant events, thus capturing weak signals more effectively. While text mining encompasses diverse methodologies that can potentially enhance scanning, the selection and application of these methodologies are crucial. For instance, semantic analysis can identify topics that are related to others but not frequently discussed. This highlights the need for a scanning process that involves experts who are proficient in both foresight and text mining, capable of framing the right questions and interpreting the data accurately. Emerging technologies like ChatGPT also show promise in this area, but effective utilization requires a deep understanding of both the tool and the foresight process, also in the light of the existing problems related to "hallucination", or data fabrication and falsification, generative AI tools are burdened with (Emsley, 2023).

Text mining, though useful for identifying major trends, may have not captured the breadth of forces at play due to the limited scope of analyzed records. Increasing the number of records might improve results, but weak signals could still be overlooked. Therefore, text mining is beneficial for short-term horizon scanning for identifying probable futures but requires complementary methods for exploring plausible and possible futures (Gall et al., 2022). Text mining was also able to gather different trends compared to those identified through extensive reading, highlighting the potential of this method to reveal overlooked topics. It would be valuable to understand why certain topics identified by text mining were not included through extensive reading. This discrepancy suggests that the reference framework of researchers might have inadvertently overlooked such information. Therefore, it would be interesting to explore these dynamics further, investigating why certain forces of change were not gathered through extensive reading.

Different sources provide varying insights. Academic reports offer in-depth analysis of well-established trends, non-academic articles often highlight speculative and emerging trends, and industry reports focus on driving forces and business changes. Therefore, a careful mix of sources should be selected based on the information needs of the foresight exercise.

Our findings also offer practical implications for foresight practitioners. For short-term foresight focusing on well-known trends, text mining proves effective. For instance, significant trends like the use of the metaverse in surgical training and mental health treatments could be identified through text mining (MetaMedics, 2023). However, less discussed topics, such as the environmental impact of metaverse applications and data security concerns, are better identified through extensive reading. When analyzing non-academic articles, different emerging topics can be identified, which may not yet be validated through academic literature, such as advances in digital health still in the clinical trial phase. This approach is particularly relevant for longer time horizons where weak signals are crucial for identifying possible and plausible futures. Similarly, industry reports are valuable for addressing uncertainties. The immersive experience and the ease of data sharing enabled by the metaverse still have blurred boundaries, requiring further research to understand the benefits of the patient-centric approach it promotes. Both the topic and the method should be therefore chosen based on the time horizon and the type of information needed.

In technology foresight, industry reports on technological fields are highly effective as they examine diverse topics and investment areas, providing insights from various fields. However, to obtain a holistic picture, it is essential to integrate multiple sources, since reports have the advantage to effectively capture emerging trends and hot topics, while they may lack the rigor characterizing academic sources, which commonly rely on the scientific method and are subject to the peer review process before publication. Ethical challenges and institutional topics are consistently difficult to capture, regardless of the source. Therefore, specific attention must be given to these dimensions to avoid overlooking them. The careful selection of sources and methods based on the objectives of the foresight exercise is crucial for obtaining comprehensive and insightful results.

6. Conclusion

The objective of this article is to understand the different informative potentialities that sources and methods have in the process of foresight, especially in relation to the scanning phase. Our findings indicate that different sources and methods yield distinct results. Extensive reading allows for a deep understanding and identification of weak signals, while text mining efficiently processes large datasets, identifying prevalent trends but potentially missing less frequent, yet significant, changes. Moreover, academic sources tend to focus on well-established trends, non-academic articles are more speculative and highlight emerging trends, and reports often emphasize driving forces and business implications. Thus, the selection of sources and methods should align with the specific objectives of the foresight exercise.

However, this study has limitations. To compare the forces of change from different sources, we set clear boundaries in our research, focusing specifically on the metaverse and healthcare. As a result, some relevant forces of change that arise from cross-boundary areas among different fields may have been overlooked. This constraint highlights the need for a broader, more integrative approach in future studies to capture a wider array of emerging forces of change.

Future research in the field of foresight should explore how experts integrate and utilize the results obtained from both extensive reading and text mining methodologies. Understanding how experts interpret and build upon the insights gleaned from these diverse approaches could shed light on the complementary strengths and limitations of each method. Particularly intriguing is the investigation into whether the initial input data quality and quantity influence experts' ability to overcome inherent biases in foresight exercises. Exploring these dynamics can provide valuable insights into optimizing methodological combinations for more robust foresight outcomes. Additionally, an interesting avenue for future inquiry would be to examine the scalability of text mining by increasing the volume of records analyzed. This exploration could elucidate whether text mining, through its capacity to process larger datasets efficiently, can capture a comprehensive spectrum of forces of change, including subtle weak signals that may otherwise go unnoticed.

CRediT authorship contribution statement

Francesca Zoccarato: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giovanni Toletti:** Writing – original draft, Supervision, Methodology. **Emanuele Lettieri:** Methodology, Formal analysis, Conceptualization. **Antonio Ghezzi:** Writing – original draft, Visualization, Validation, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Ali, O., Momin, M., Shrestha, A., Das, R., Alhajj, F., & Dwivedi, Y. K. (2023). A review of the key challenges of non-fungible tokens. *Technological Forecasting and Social Change, 187*, Article 122248. https://doi.org/10.1016/j.techfore.2022.122248

Amorim-Lopes, M., Oliveira, M., Raposo, M., Cardoso-Grilo, T., Alvarenga, A., Barbas, M., Alves, M., Vieira, A., & Barbosa-Póvoa, A. (2021). Enhancing optimization planning models for health human resources management with foresight. *Omega, 103*, Article 102384. https://doi.org/10.1016/j.omega.2020.102384
Apreda, R., Bonaccorsi, A., dell'Orletta, F., & Fantoni, G. (2019). Expert forecast and realized outcomes in technology foresight. *Technological Forecasting and Social Change, 141*, 277–288. https://doi.org/10.1016/j.techfore.2018.12.006
Behkami, N. A., & U. Daim, T. (2012). Research Forecasting for Health Information Technology (HIT), using technology intelligence. *Technological Forecasting and Social Change, 79*(3), 498–508. https://doi.org/10.1016/j.techfore.2011.08.015
Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM, 55*(4), 77–84. https://doi.org/10.1145/2133806.2133826
Blei, David M., Ng, Andrew Y., & Jordan, Michael I. (2003). *Latent Dirichlet Allocation, 3*, 993–1022.
Boe-Lillegraven, S., & Monterde, S. (2015). Exploring the cognitive value of technology foresight: The case of the Cisco Technology Radar. *Technological Forecasting and Social Change, 101*, 62–82. https://doi.org/10.1016/j.techfore.2014.07.014
Bonaccorsi, A., Apreda, R., & Fantoni, G. (2020). Expert biases in technology foresight. Why they are a problem and how to mitigate them. *Technological Forecasting and Social Change, 151*, Article 119855. https://doi.org/10.1016/j.techfore.2019.119855
Chen, D., & Zhang, R. (2022). Exploring research trends of emerging technologies in health metaverse: A bibliometric analysis. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3998068
Chin, T., Shi, Y., Singh, S. K., Agbanyo, G. K., & Ferraris, A. (2022). Leveraging blockchain technology for green innovation in ecosystem-based business models: A dynamic capability of values appropriation. *Technological Forecasting and Social Change, 183*, Article 121908. https://doi.org/10.1016/j.techfore.2022.121908
Costa Climent, R., & Haftor, D. M. (2021). Business model theory-based prediction of digital technology use: An empirical assessment. *Technological Forecasting and Social Change, 173*, Article 121174. https://doi.org/10.1016/j.techfore.2021.121174
Darkow, I.-L. (2015). The involvement of middle management in strategy development—Development and implementation of a foresight-based approach. *Technological Forecasting and Social Change, 101*, 10–24. https://doi.org/10.1016/j.techfore.2013.12.002
Davis, A., Murphy, J., University of Nebraska at Omaha, Owens, D., University of Nebraska at Omaha, Khazanchi, D., University of Nebraska at Omaha, Zigurs, I., & University of Nebraska at Omaha. (2009). Avatars, People, and Virtual Worlds: Foundations for Research in Metaverses. *Journal of the Association for Information Systems, 10*(2), 90–117. https://doi.org/10.17705/1jais.00183
De Miranda Santo, M., Coelho, G. M., Dos Santos, D. M., & Filho, L. F. (2006). Text mining as a valuable tool in foresight exercises: A study on nanotechnology. *Technological Forecasting and Social Change, 73*(8), 1013–1027. https://doi.org/10.1016/j.techfore.2006.05.020
Emsley, R. (2023). ChatGPT: These are not hallucinations – they're fabrications and falsifications. s41537-023-00379–4 *Schizophrenia, 9*(1), 52. https://doi.org/10.1038/s41537-023-00379-4.
Fan, W., Wallace, L., Rich, S., & Zhang, Z. (2006). Tapping the power of text mining. *Communications of the ACM, 49*(9), 76–82. https://doi.org/10.1145/1151030.1151032
Flick, C., Zamani, E. D., Stahl, B. C., & Brem, A. (2020). The future of ICT for health and ageing: Unveiling ethical and social issues through horizon scanning foresight. *Technological Forecasting and Social Change, 155*, Article 119995. https://doi.org/10.1016/j.techfore.2020.119995
Gall, T., Vallet, F., & Yannou, B. (2022). How to visualise futures studies concepts: Revision of the futures cone. *Futures, 143*, Article 103024. https://doi.org/10.1016/j.futures.2022.103024
Hakmaoui, A., Oubrich, M., Calof, J., & El Ghazi, H. (2022). Towards an anticipatory system incorporating corporate foresight and competitive intelligence in creating knowledge: A longitudinal Moroccan bank case study. *Technological Forecasting and Social Change, 174*, Article 121139. https://doi.org/10.1016/j.techfore.2021.121139
Heger, T., & Rohrbeck, R. (2012). Strategic foresight for collaborative exploration of new business fields. *Technological Forecasting and Social Change, 79*(5), 819–831. https://doi.org/10.1016/j.techfore.2011.11.003
Herrera-Aliaga, E., & Estrada, L. D. (2022). Trends and innovations of simulation for twenty first century medical education. *Frontiers in Public Health, 10*, Article 619769. https://doi.org/10.3389/fpubh.2022.619769
Hines, A. (2020). Evolution of framework foresight. *Foresight, 22*(5/6), 643–651. https://doi.org/10.1108/FS-03-2020-0018
Hirsch, I. B., Nardacci, E., & Verderese, C. A. (2019). Flash continuous glucose monitoring: Implications for use of continuous data in daily diabetes management. *Diabetes Spectrum, 32*(4), 355–367. https://doi.org/10.2337/ds18-0059
Idoko, O., & MacKay, R. B. (2021). The performativity of strategic foresight tools: Horizon scanning as an activation device in strategy formation within a UK financial institution. *Technological Forecasting and Social Change, 162*, Article 120389. https://doi.org/10.1016/j.techfore.2020.120389
Inkinen, T., Helminen, R., & Saarikoski, J. (2021). Technological trajectories and scenarios in seaport digitalization. *Research in Transportation Business Management, 41*, Article 100633. https://doi.org/10.1016/j.rtbm.2021.100633
Jan, M. A., Cai, J., Gao, X.-C., Khan, F., Mastorakis, S., Usman, M., Alazab, M., & Watters, P. (2021). Security and blockchain convergence with Internet of Multimedia Things: Current trends, research challenges and future directions. *Journal of Network and Computer Applications, 175*, Article 102918. https://doi.org/10.1016/j.jnca.2020.102918
Kayser, V., & Blind, K. (2017). Extending the knowledge base of foresight: The contribution of text mining. *Technological Forecasting and Social Change, 116*, 208–215. https://doi.org/10.1016/j.techfore.2016.10.017
Kayser, V., & Shala, E. (2020). Scenario development using web mining for outlining technology futures. *Technological Forecasting and Social Change, 156*, Article 120086. https://doi.org/10.1016/j.techfore.2020.120086
Kim, S., Connerton, T. P., & Park, C. (2021). Exploring the impact of technological disruptions in the automotive retail: A futures studies and systems thinking approach based on causal layered analysis and causal loop diagram. *Technological Forecasting and Social Change, 172*, Article 121024. https://doi.org/10.1016/j.techfore.2021.121024
Ko, B. K., & Yang, J.-S. (2024). Developments and challenges of foresight evaluation: Review of the past 30 years of research. *Futures, 155*, Article 103291. https://doi.org/10.1016/j.futures.2023.103291
KPMG. (2020). *Connected Health: The new reality for healthcare*.
Kwon, H., Kim, J., & Park, Y. (2017). Applying LSA text mining technique in envisioning social impacts of emerging technologies: The case of drone technology. *Technovation, 60–61*, 15–28. https://doi.org/10.1016/j.technovation.2017.01.001
Lee, L.-H., Braud, T., Zhou, P., Wang, L., Xu, D., Lin, Z., Kumar, A., Bermejo, C., & Hui, P. (2021). All One Needs to Know about Metaverse: A Complete Survey on Technological Singularity, Virtual Ecosystem, and Research Agenda (arXiv:2110.05352). arXiv. http://arxiv.org/abs/2110.05352.
Lehr, T., Lorenz, U., Willert, M., & Rohrbeck, R. (2017). Scenario-based strategizing: Advancing the applicability in strategists' teams. *Technological Forecasting and Social Change, 124*, 214–224. https://doi.org/10.1016/j.techfore.2017.06.026
Li, X., Xie, Q., Daim, T., & Huang, L. (2019). Forecasting technology trends using text mining of the gaps between science and technology: The case of perovskite solar cell technology. *Technological Forecasting and Social Change, 146*, 432–449. https://doi.org/10.1016/j.techfore.2019.01.012
Li, X., Xie, Q., Jiang, J., Zhou, Y., & Huang, L. (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*, 687–705. https://doi.org/10.1016/j.techfore.2018.06.004
Li, X., Zhou, Y., Xue, L., & Huang, L. (2015). Integrating bibliometrics and roadmapping methods: A case of dye-sensitized solar cell technology-based industry in China. *Technological Forecasting and Social Change, 97*, 205–222. https://doi.org/10.1016/j.techfore.2014.05.007
Madani, F., & Weber, C. (2016). The evolution of patent mining: Applying bibliometrics analysis and keyword network analysis. *World Patent Information, 46*, 32–48. https://doi.org/10.1016/j.wpi.2016.05.008
Maresch, D., & Gartner, J. (2020). Make disruptive technological change happen—The case of additive manufacturing. *Technological Forecasting and Social Change, 155*, Article 119216. https://doi.org/10.1016/j.techfore.2018.02.009
Marinković, M., Al-Tabbaa, O., Khan, Z., & Wu, J. (2022). Corporate foresight: A systematic literature review and future research trajectories. *Journal of Business Research, 144*, 289–311. https://doi.org/10.1016/j.jbusres.2022.01.097

Martin, B. R. (1995). Foresight in science and technology. *Technology Analysis Strategic Management, 7*(2), 139–168. https://doi.org/10.1080/09537329508524202

MetaMedics, Last accessed: June 2023. https://metamedicsvr.com/vr-nursing/.

Metz, A., & Hartley, P. (2020). Scenario development as valuation: Opportunities for reflexivity. *Technological Forecasting and Social Change, 155*, Article 120027. https://doi.org/10.1016/j.techfore.2020.120027

Mozumder, M. A. I., Sheeraz, M. M., Athar, A., Aich, S., & Kim, H.-C. (2022). Overview: Technology Roadmap of the Future Trend of Metaverse based on IoT, Blockchain, AI Technique, and Medical Domain Metaverse Activity. *2022 24th International Conference on Advanced Communication Technology (ICACT)*, 256–261. https://doi.org/10.23919/ICACT53585.2022.9728808

Pandian, G. S. B., Jain, A., Raza, Q., & Sahu, K. K. (2021). Digital health interventions (DHI) for the treatment of attention deficit hyperactivity disorder (ADHD) in children—A comparative review of literature among various treatment and DHI. *Psychiatry Research, 297*, Article 113742. https://doi.org/10.1016/j.psychres.2021.113742

Plechatá, A., Makransky, G., & Böhm, R. (2022). Can extended reality in the metaverse revolutionise health communication? *Npj Digital Medicine, 5*(1), 132. https://doi.org/10.1038/s41746-022-00682-x

Popper, R. (2008). How are foresight methods selected? *Foresight, 10*(6), 62–89. https://doi.org/10.1108/14636680810918586

Popper, A. (2015). Transforming Business through Science Fiction Prototyping. *Computer, 48*(1), 70–72. https://doi.org/10.1109/MC.2015.30

Rohrbeck, R., & Kum, M. E. (2018). Corporate foresight and its impact on firm performance: A longitudinal analysis. *Technological Forecasting and Social Change, 129*, 105–116. https://doi.org/10.1016/j.techfore.2017.12.013

Rohrbeck, R., Thom, N., & Arnold, H. (2015). IT tools for foresight: The integrated insight and response system of Deutsche Telekom Innovation Laboratories. *Technological Forecasting and Social Change, 97*, 115–126. https://doi.org/10.1016/j.techfore.2013.09.015

Ruiz Mejia, J.M., & Rawat, D.B. (2022). Recent Advances in a Medical Domain Metaverse: Status, Challenges, and Perspective. 2022 Thirteenth International Conference on Ubiquitous and Future Networks (ICUFN), 357–362. https://doi.org/10.1109/ICUFN55119.2022.9829645.

Saritas, O., Burmaoglu, S., & Ozdemir, D. (2022). The evolution of Foresight: What evidence is there in scientific publications? *Futures, 137*, Article 102916. https://doi.org/10.1016/j.futures.2022.102916

Saritas, O., & Smith, J. E. (2011). The Big Picture – trends, drivers, wild cards, discontinuities and weak signals. *Futures, 43*(3), 292–312. https://doi.org/10.1016/j.futures.2010.11.007

Schiavone, F., Mancini, D., Leone, D., & Lavorato, D. (2021). Digital business models and ridesharing for value co-creation in healthcare: A multi-stakeholder ecosystem analysis. *Technological Forecasting and Social Change, 166*, Article 120647. https://doi.org/10.1016/j.techfore.2021.120647

Sestino, A., & D'Angelo, A. (2023). My doctor is an avatar! The effect of anthropomorphism and emotional receptivity on individuals' intention to use digital-based healthcare services. *Technological Forecasting and Social Change, 191*, Article 122505. https://doi.org/10.1016/j.techfore.2023.122505

Statista. (2023, maggio). Metaverse Health and Fitness. https://www.statista.com/outlook/amo/metaverse/metaverse-health-and-fitness/worldwide.

Stowe Higgs, E. (1990). The landscape evolution model: A case for a paradigmatic view of technology. *Technology in Society, 12*(4), 479–505. https://doi.org/10.1016/0160-791X(90)90016-6

Thomason, J. (2021). *MetaHealth—How will the Metaverse Change*. Health Care?

Van Wyk, R. J. (1997). Strategic technology scanning. *Technological Forecasting and Social Change, 55*(1), 21–38. https://doi.org/10.1016/S0040-1625(97)83077-6

Wang, Y., Su, Z., Zhang, N., Xing, R., Liu, D., Luan, T. H., & Shen, X. (2022). A survey on metaverse: Fundamentals,security, and privacy, 1–1 *IEEE Communications Surveys Tutorials*. https://doi.org/10.1109/COMST.2022.3202047.

Zeng, M. A. (2018). Foresight by online communities – The case of renewable energies. *Technological Forecasting and Social Change, 129*, 27–42. https://doi.org/10.1016/j.techfore.2018.01.016

Zhang, M., Ding, H., Naumceska, M., & Zhang, Y. (2022). Virtual Reality Technology as an Educational and Intervention Tool for Children with Autism Spectrum Disorder: Current Perspectives and Future Directions. *Behavioral Sciences, 12*(5), 138. https://doi.org/10.3390/bs12050138

Zhang-Zhang, Y., Rohlfer, S., & Varma, A. (2022). Strategic people management in contemporary highly dynamic VUCA contexts: A knowledge worker perspective. *Journal of Business Research, 144*, 587–598. https://doi.org/10.1016/j.jbusres.2021.12.069

Zou, Y., Meng, T., Zhang, P., Zhang, W., & Li, H. (2020). Focus on blockchain: A comprehensive survey on academic and application. *IEEE Access, 8*, 187182–187201. https://doi.org/10.1109/ACCESS.2020.3030491