Enhancing Strategic Decision-Making through Integrated Visual Analytics: A Study on the Identification and Utilization of Emerging Technological Trends

1st Weiqiang Ying*
School of Art and Archaeologyn
Hangzhou City University
Hangzhou, China
11921165@zju.edu.cn

2nd Lingyan Zhang
College of Computer Science and Technology
Zhejiang University
Hangzhou, China
zhlingyan@zju.edu.cn

3rd Lanqing Huang
Zhejiang University
Hangzhou, China
huanglanqing3@163.com

Abstract—**Technological progress exerts a decisive influence on corporate strategic decision-making, particularly within the rapidly evolving domain of science and technology. Early identification and adoption of emerging technological trends are pivotal for enterprises to sustain competitive advantage and market position. However, many innovative companies fail to fully leverage the potential of their products and technologies due to the absence of a systematic approach. To counter this challenge, large corporations have established forward-looking departments dedicated to forecasting future trends and innovation. Despite this, the current predictive process integrates human intelligence with machine learning methods, and the visual analysis that combines these two forms of intelligence holds immense potential. This paper introduces an integrated method that combines information visualization, trend mining, and interactive design, aimed at supporting users in exploring, detecting, and identifying emerging technological trends within complex datasets. The method facilitates in-depth trend analysis and extraction of meaningful insights from data through an interactive visual representation system. Moreover, the integration of interactive design throughout the analytical process is crucial for supporting the analytical process in technology and innovation management [8]. A literature review, trend visualization, interactive visualization, and interactive design methods are essential for understanding the context of technology management and visualization analysis systems. The interactive design approach places special emphasis on the central role of users in the design process, ensuring that the system meets user needs and supports effective identification and utilization of emerging technological trends.The research findings indicate that the integration of human intelligence and machine learning methods can enhance the accuracy and efficiency of predicting future technological trends. The interactive design-based method proposed in this paper not only augments and expands previous methods of technology and design management trend analysis but also introduces novel interactive designs, providing more suitable interactive methods for technology foresight and innovation detection. These methods and tools enable enterprises to more effectively respond to market changes, grasp technological trends, and make informed strategic decisions.**

Keywords—Technological Development, Strategic Decision-Making, Emerging Trends, Interactive Design, Visualization Techniques, Trend Mining

I. INTRODUCTION

With the continuous advancement of Artificial Intelligence (AI) and Machine Learning (ML) technologies, their capabilities in data analysis and forecasting are also continuously being enhanced, providing more accurate decision support for users and strategic decision-making for enterprises. This has profound implications for corporate competitiveness and market positioning[1]. In the field of design management, the rapid development of technology is driving the realization of personalized and adaptive systems, which are becoming more intelligent and better able to meet user needs. Early identification and adoption of new technology trends are crucial for enterprises to maintain a leading position. However, many innovative companies may overlook the development of emerging technologies due to the lack of a systematic approach, thus failing to fully leverage the potential of their products or technologies[2]. To address this challenge, some large enterprises have established forward-looking departments focused on predicting future development trends and innovation [3]. Despite the significant role these forward-looking departments play in forecasting future trends, the integration of human intelligence and machine learning methods in the prediction process is rarely achieved[4, 5].

Currently, although most information retrieval systems employ different methods to extract trends from text, they fall short in providing relevant visual representations that effectively support users in exploring, identifying, detecting, and inferring significant trends in the future development of technology[6]. Therefore, to effectively identify and utilize emerging trends, a method is needed that provides an interactive overview of data, adapts to ongoing changes in data, and allows users to gain insights through data exploration[7].

Personalized systems offer customized experiences by learning user behavior and preferences. Adaptive systems, on the other hand, can automatically adjust their behavior in response to environmental changes or user input. The development of these systems, as explored by Ogiela, Marek

R. [8], is making design management tools more intelligent, thereby serving users more effectively.

The application of AI and ML has permeated multiple aspects of design management. For instance, sentiment analysis can evaluate public opinion on design, as studied by Vohra, A. et al. [5, 9]. Keyword extraction and topic modeling techniques such as TF-IDF and LDA are helping to extract valuable information from large volumes of text data, which has particular application potential in extracting and classifying sentiment tendencies from text data in the healthcare field, helping professionals and companies to assess drug safety and enhance patient trust. Eysha Saad et al., by combining these two methods, used tools such as AFFIN, TextBlob, and VADER for sentiment lexicon annotation, and applied feature engineering techniques such as term frequency (TF), term frequency-inverse document frequency (TF-IDF), and machine learning models such as logistic regression (LR), AdaBoost classifier (AB), random forest (RF), extra trees classifier (ETC), and multilayer perceptron (MLP) for sentiment classification. The experimental results show that the hybrid method outperforms single methods, with TextBlob combined with TF-IDF and MLP achieving an accuracy rate of 96%, demonstrating the efficiency and application prospects of sentiment analysis in medical text processing[10].

The interdisciplinary integration of design management has led the field to combine technologies and methods from different disciplines. This integration enhances the comprehensiveness and depth of decision-making, as shown in the research by Hamed Taherdoost [11].

The development of real-time data streams and dynamic visualization tools, as described by George Chin et al. [12], allows users to acquire and analyze data more quickly, accelerating the decision-making process. The application of AR and VR technologies provides a more immersive experience for design management. These technologies help users understand data and information in a more intuitive way, as explored by Farzad Pour Rahimian[13] in his research on integrating BIM data into immersive VR and AR environments to simplify the design process and provide a streamlined agnostic openBIM system.

Furthermore, the inclusion of interactive design throughout the analysis process is crucial for supporting the analytical process in technology and innovation management [14]. This paper will explore the application of interactive design methods in technology and innovation management, as well as how to improve the accuracy and efficiency of predicting future technology trends by integrating human intelligence and machine learning methods.

In the field of technology and innovation management, literature reviews, trend visualization, interactive visualization, and interactive design methods are essential for understanding the background of the introduced technology management and visualization analysis systems[1]. Literature reviews provide a comprehensive understanding of existing research, helping to identify gaps and challenges in the research field. Trend visualization helps users quickly identify patterns and trends by transforming complex data into intuitive graphical representations. Interactive visualization further enhances this process by allowing users to interact with data, thereby gaining deeper insights.

The application of interactive design methods is particularly important in technology and innovation management [15]. This approach emphasizes the central role of users in the design process, ensuring that the system can meet the needs and expectations of users. In the context of technology and innovation management, interactive design methods need to pay special attention to the analytical process to support users in effectively identifying and utilizing emerging technology trends.

Although previous studies have explored the application of information retrieval systems in trend extraction[6], existing systems have limitations in providing visual representations that can support users in exploring and inferring future technological developments. To overcome these limitations, new interactive design methods need to be developed that can integrate human intelligence and machine learning methods to improve the accuracy and efficiency of predicting future technology trends.

The field of design management is continuously evolving and innovating under the impetus of technology. From trend mining techniques to machine learning methods in interactive design, to data visualization techniques, and the application of probabilistic topic models, the comprehensive use of these technologies provides users with better data analysis and decision support. With the further development of personalized and adaptive systems, and the continuous advancement of AI and ML technologies, design management tools will become more intelligent, better able to meet user needs, and provide deeper data analysis and forecasting capabilities.

This paper proposes an interactive design-based method combined with information visualization and trend mining to support users in exploring, detecting, and identifying emerging technology trends in complex datasets. Through this method, enterprises can more effectively respond to market changes, grasp technological trends, and make wise strategic decisions.

II. METHODS

The method introduced in this paper utilizes trend mining approaches derived from textual data, as well as the visualization of trends and text. Consequently, we present related work in the areas of trend mining and the visualization of trends in conjunction with text, and endeavor to connect aspects of technology and innovation to bridge the domains of analysis, visualization, and technology management in order to gather a more appropriate interactive design landscape.

A. Trend mining from text

Identifying trends within textual data is a pivotal aspect of text mining, also known as Textual Knowledge Discovery (TKD). This process encompasses the extraction of key topics and patterns from textual documents to comprehend their significance over time [16]. Various methods, such as sequential pattern mining and trend graphs, are commonly employed to uncover textual trends. For instance, Pecman et al. define trends as sequences of frequent phrases that aid in identifying recurring patterns within textual information[17].

Khan et al. introduced the concept of trend graphs, which depict the evolution of term relationships within a specific context in a corpus[18]. They also presented the use of context graphs to visualize the developmental trends in textual data. Sciascio et al. developed an Information Quality (IQ) toolkit for the automatic trend detection of online content [19], while Bharath Bhushan and Nicolas proposed two distinct approaches to identify evolving topics within textual data[20, 21].

Cao et al. utilized clustering algorithms to extract both short-term and long-term topics from textual data, revealing popular topic trends[22]. Similarly, Cammarano et al. proposed a novel method for detecting technological trends in patent documents, assisting in tracking innovation within specific industries[23, 24]. Oralbekova et al. delved into natural language processing and topic modeling to conduct a comprehensive study of the entire conversation process [25, 26].

The combination of these diverse methods and tools plays a crucial role in revealing complex patterns and trends within textual data, thereby enabling informed decision-making and providing a comprehensive insight into the evolution of topics over time.

B. *Trend and text visualization*

Trend mining methods are becoming increasingly important across various domains as they provide valuable metrics for detecting trends within data. While these methods are useful for identifying patterns and trends, the human capacity for knowledge acquisition remains crucial for making informed decisions based on these trends.

The representation of trends plays a pivotal role in trend analysis as it enables users to understand and interpret the underlying patterns in the data. Basic visualization techniques, such as line charts and word clouds, are commonly used to visually represent trends. Line charts are effective in displaying the trends of variables over time, while word clouds are used to highlight important keywords or terms in text-based datasets.

Different systems employ various visualization methods to present data trends. For instance, temporal data visualization is used to analyze dependent variables that change over time, with time as the independent variable [27], whereas Scaccia et al. have utilized Natural Language Processing (NLP) methods, which are becoming a valuable strategy for content analysis of academic literature, applying NLP to identify publication trends in the journal Implementation Science [28]. On the other hand, visualization techniques such as word clouds and bar charts are combined to present data trends.

By visualizing trends in this manner, users can gain insights into the evolution of topics over time and make informed decisions based on the analysis.

A literature review reveals a variety of algorithms and visualization methods used to extract trends from textual data. However, there is currently a lack of an interactive visual representation system that can perform in-depth analysis of trends. Such a system would enable users to explore the trends in data from different perspectives and extract meaningful insights from the data.

In summary, trend mining methods and visualization techniques are fundamental tools for analyzing data trends. By combining automated trend mining methods with human capacity for knowledge acquisition, organizations can make more informed decisions based on the insights gained from trend analysis.

III. DATA AND MODELS

A. *General process*

In the context of technology, the objective of trend analysis is to achieve an exploratory visualization approach that identifies trends and their future potential in a graphical manner. This method emphasizes the dynamic and interactive exploration and analysis of trends by allowing users to view data from various perspectives. In the analysis of technological trends, the focus is on addressing key questions, such as when a particular technology emerged, who the key players in the industry are, what the core themes surrounding that technology are, and how the technology will evolve in the future. By addressing these questions, trend analysis provides valuable insights into the technological landscape and assists organizations in making informed decisions regarding technology adoption and innovation strategies,as show in figure1.

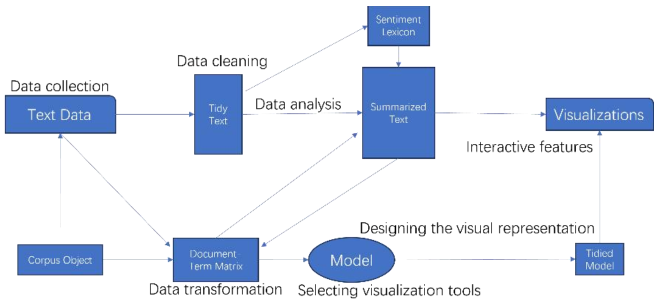

Fig. 1. Our transformation process from raw data to interactive visual representations consisting of seven main steps (adapted from[29]). The transformation process is described in the following section more detailed

By summarizing the current core themes and exploring the possible causes of trends through navigation and analysis from different perspectives, this approach enables researchers and practitioners to identify potential patterns and the drivers of trends, allowing them to make data-driven decisions based on the analysis.

For instance, by utilizing the DBLP database [30] to analyze publication trends in the field of computer science, researchers can gain insights into emerging technologies, key research areas, and influential authors within the domain. Of course, the selection of using DBLP for data collection is also challenging due to the fact that the DBLP indexing database does not provide abstracts or full texts.

Research publications play a crucial role in identifying new technologies at an early prototyping stage. While patents and online news often indicate that new technologies have hit the market, research publications introduce cutting-edge technologies that are still in development. By analyzing research publications, organizations can stay ahead of technological advancements and actively respond to emerging trends in their respective industries. The rapid development of new technological fields and the emergence of new journals serve as venues for the exchange of research methods and discoveries. The Emerging Sources Citation Index (ESCI) expands the scope of journals, providing visibility to important regional journals and new trends, facilitating communication and research assessment, but its impact is limited in non-English speaking countries, and the selection of journals still needs to be balanced[31].

In summary, technological trend analysis using exploratory visualization techniques and problem-based analysis provides valuable insights into the technological landscape, assisting organizations in making informed decisions regarding technology adoption and innovation strategies.

B. Data collection

Our server-side adopts an indexed database, with the initial data source from DBLP, providing basic metadata for computer science. Each document has a unique DOI, which can be used to identify and enrich data entities from additional data sources. The initial data is stored in a relational database, and enriched data is stored in a database for identifying and modeling topics. Our data model is used to select visualization structures, with the final use of appropriate interactive or side-by-side visualization dashboards. Each DOI is sent to all publishers, and documents without a DOI are identified using the title and author's name.

C. Data cleaning

Data quality is an important aspect of the data analysis field, as the accuracy and reliability of data directly affect the validity of the analysis results. To ensure proper data quality, data enhancement techniques must be employed, which involves collecting additional data from various online sources to improve the quality of the existing dataset[32].

The foundational dataset used in this study is a combination of multiple datasets, each providing different quality and quantities of metadata. Initially, a dataset from the Digital Bibliography & Library Project (DBLP) was used, consisting of approximately 6 million entries but lacking textual content.

To enrich the data, the system employed a method that includes identifying the location of specific data resources on the internet and collecting additional information about specific publications. Each Digital Object Identifier (DOI) associated with a publication is sent to the publisher to obtain more information. In cases where a DOI is not available, documents are identified online using the title and author's name. Further information about publications is collected through web services or crawling techniques. Web services typically provide comprehensive information about publications, while crawling techniques involve developing strategies for web crawling and cleaning the obtained data.

Data cleaning techniques are then applied to address issues such as duplicate entries, missing data, and incorrect information [33]. Through this process, the data in DBLP is enriched with metadata, including abstracts, full-text articles, and citation information. This is done to identify the most relevant papers in a specific field based on the number of citations they have received.

In summary, data augmentation, data enrichment, and data cleaning are necessary steps to improve the quality of the data for analysis. By using these techniques, researchers can ensure that the data used for analysis is accurate, reliable, and comprehensive.

D. Data transformation

Data Transformation Significant progress has been made in recent years in the field of natural language processing and information retrieval by leveraging probabilistic topic models. By utilizing abstracts from most entries in the Digital Bibliography & Library Project (DBLP) database and some open-access full texts from various sources, researchers have been able to extract valuable information from textual data to generate coherent topics. This approach has allowed a deeper understanding of the content within documents and has shown promising results in document similarity assessment. One of the key methods employed in this study is the probabilistic topic model, which has advantages over traditional topic title systems in evaluating document similarity. By implementing the Latent Dirichlet Allocation (LDA) algorithm, researchers have been able to automatically categorize and assign topics to documents, with the accuracy of the final model depending on the number of documents processed [34, 35].

Each document is assigned to one or more topics, with each topic typically represented by the top 20 words in N-Gram form and a phrase. After 4,000 iterations of the LDA algorithm, 500 topics are generated, which are used to filter the results of faceted shape searches and create topic models. It has been observed that the topics generated using LDA exhibit good consistency in most cases, thereby improving the overall quality of the topic modeling process[36].

In summary, the application of probabilistic topic models, particularly the LDA algorithm, has proven to be an effective tool for extracting meaningful topics from textual data and improving document similarity assessment. This approach has the potential to revolutionize information retrieval systems by facilitating more accurate and coherent topic modeling.

E. Trend identification

Yubin Qian employed a lexicon-based hybrid approach, integrating the stems of corporate culture keywords extracted by the bag-of-words model into the Latent Dirichlet Allocation (LDA) model, to explore new avenues for mining corporate culture [37]. By analyzing two independent corpora, the effectiveness of this method in distinguishing corporate values and identifying cultural types was verified, providing a novel perspective for understanding the cultural dimensions within specialized discourse.

A document may encompass multiple topics, with each word in the document being generated by one of these topics. It is a topic model that can present the topics of each document in a document collection in the form of a probabilistic distribution (Table 1); it is also an unsupervised learning algorithm that does not require a manually annotated training set during training, requiring only a collection of documents and a specified number of topics; moreover, another advantage of LDA is that for each topic, a set of words can be identified to describe it; Table 1 displays the actual number published every four years. Therefore, the normalization of topic frequency is the first step in obtaining the true trend over time. We calculate the normalized topic frequency by normalizing the number of documents containing a particular topic within a year.

Assuming that a topic appears with a frequency of f_t within a year, and the maximum frequency of all topics within that year is f_{max}, then the normalized frequency of the topic can be calculated as:

$$TF(t) = \frac{f(t)}{f_{max}}$$

Where:

TF(t) is the normalized frequency of topic t

f(t) is the frequency of topic t

fmax is the maximum frequency among all topics Using this formula, the normalized frequency value of a topic for a given year can be calculated.

TABLE I. NUMBER OF PUBLICATIONS IN DBLP

	Documents in DBLP						
Years	1999	2003	2007	2011	2015	2019	2023
Documents	71220	116519	189891	251259	303403	418938	492263
https://dblp.org/statistics/publicationsperyear.html							

The average of the Dirichlet normalized topic frequency can be calculated using the expected value of the Dirichlet distribution. Assuming the Dirichlet distribution parameters for topic frequencies are α, and the i-th value in the Dirichlet normalized frequency for a topic is θ_i, then the average value of this can be expressed as:

$$E[\theta_i] = \frac{\alpha_i}{\Sigma(\alpha)} \quad 2$$

Where, E[θ_i] represents the average of the i-th Dirichlet normalized frequency, α_i represents the i-th value in the Dirichlet distribution parameter α, and ∑(α) represents the sum of all values in α.

By calculating the average of the Dirichlet normalized topic frequency, a better understanding of the frequency distribution of the topics can be achieved, allowing for a more in-depth analysis and understanding of the topics.

Divide the documents of each year into fixed-length periods and calculate the regression of the normalized topic frequency.

Define the length of the period (e.g., monthly, quarterly, etc.), and divide the documents of each year according to this period.

For each period, calculate the number of documents containing a certain topic and calculate the normalized topic frequency using the formula (1) mentioned above.

Use the normalized topic frequency of each period as a data point to form a regression model, which can be modeled using linear regression, polynomial regression, and other methods. To calculate the regression formula for the normalized topic frequency, linear regression or other regression methods can be used. The following is the calculation formula for linear regression:

Assuming there are n sample data points, represented as (x1, y1), (x2, y2), ..., (xn, yn), where xi is the independent variable (time or period), and yi is the normalized topic frequency.

The linear regression model is assumed to be: y = β0 + β1*x,

where β0 is the intercept, and β1 is the slope.

To calculate the regression formula, the estimated values of β1 (slope) and β0 (intercept) need to be calculated first:

$$\beta_1 = \Sigma((x_i - x\_mean) * (y_i - y\_mean))/\Sigma((x_i - x\_mean)^2) \quad 3$$

$$\beta_0 = y\_mean - \beta_1 * x\_mean \quad 4$$

Where, x_mean and y_mean are the average values of the independent variable and dependent variable, respectively. After obtaining β_0 and β_1, the regression equation can be obtained as:

$$\mathrm{y} = \beta 0 + \beta 1 * \mathrm{x} \quad 5$$

By fitting the linear regression model, the regression formula for the normalized topic frequency can be obtained, which helps to analyze the change trends of topics over different times or periods. If other regression methods are needed, suitable regression models can be selected according to the specific situation, and the corresponding regression formulas can be calculated. Analyzing the fit of the regression model and the trend of topic frequency changes over time can lead to the popularity changes of topics in different time periods. Through the above steps, the normalized frequency of topics in different time periods can be analyzed through regression to reveal the trends and patterns of topics over time. Weight the topic slopes of each period through weighting, and calculate the final topic weights using the determination coefficient and weights. The normalization coefficient of the Dirichlet distribution, also known as the normalization constant of the Dirichlet distribution, is used to ensure that the integral of the probability density function of the Dirichlet distribution over the entire space is 1. The Dirichlet distribution is a multivariate probability distribution, commonly used to represent the probability distribution of multiple random variables. The probability density function of the Dirichlet distribution is as follows:

$$f(\theta|\alpha) = (1/B(\alpha)) * \Pi\left(\theta_i^{(\alpha_i - 1)}\right) \quad 6$$

Where, θ is a vector representing the values of multiple random variables, α is the parameter vector of the Dirichlet distribution, B(α) is the normalization constant of the Dirichlet distribution, defined as:

$$B(\alpha) = \Pi(\Gamma(\alpha_i))/\Gamma\left(\Sigma(\alpha_i)\right) \quad 7$$

Where, Γ(αi) represents the gamma function, and Σ(αi) represents the sum of all elements in α.

Thus, the normalization coefficient B(α) of the Dirichlet distribution is obtained by integrating the probability density function of the Dirichlet distribution and ensuring that the integral result is 1. By integrating linear and exponential measurement values, calculate the final weight of the topic. First, perform linear and exponential regression analysis on the changes in topic frequency over time. Linear regression can reflect the linear growth or decrease trend of the topic over time, while exponential regression can reflect the nonlinear growth or decrease trend of the topic over time. Calculate the fitting values of linear regression and exponential regression separately, obtaining the linear predicted value and exponential predicted value for each period. Integrate the linear predicted value and the exponential predicted value, which can simply be the weighted sum of the two, with the weights determined according to the actual situation. Normalize the integrated value to make the final weights of different topics comparable.

The calculation of the final weight $\mathcal{w}$ can combine other factors, such as the importance of the topic, the magnitude of the amplitude, etc.

$$\mathcal{w} = \frac{w_1 * x_1 + w_2 * x_2 + \ldots + w_n * x_n}{w_1 + w_2 + \ldots + w_n} \quad 8$$

Where, w1, w2, ..., wn represent the weight coefficients corresponding to each data point, and x1, x2, ..., xn represent the corresponding data points.

Through the above steps, a comprehensive consideration of linear and exponential measurement values can be made to calculate the final weight of the topic. By combining the weighting of trends and the slopes and regression of different time periods, a more comprehensive and accurate result can be obtained.

Thus, the method of identifying trends through the weighting of trends and the slopes and regression of different time periods can provide better results, offering more accurate and comprehensive information for topic analysis and trend forecasting.

F. *Data modelling*

In the data modeling phase, an aspect-oriented data model is employed to analyze various aspects of the data, including semantic models, temporal models, geographical models, topic models, and trend models, etc. [38, 39]. These models are essential for organizing and representing data in a structured and meaningful manner.

Data enrichment and trend identification play a crucial role in the creation of the data model[40]. The publicly available location generates a semantic data model, which adds structure and semantics to the data for information extraction and visualization representation. This process enhances the understanding and usability of the data.

A temporal model is utilized for temporal visualization, mapping the year of data publication to a set of publications for that specific year[41]. This allows the creation of an overview of the temporal distribution of the overall result set, assisting in identifying patterns and trends that change over time.

The geographical data model focuses on geographical visualization, providing information about the country of origin of the authors' institutions[42]. By integrating the authors' national and topic information, the data is enriched and can be effectively represented geographically.

In summary, aspect-oriented data models, including semantic, temporal, geographical, topic, and trend models, are crucial for effectively organizing and representing data. Data enrichment and trend identification play a vital role in the creation of the data model, enhancing the understanding and visualization of the data. Temporal, geographical, topic, and trend models provide valuable insights into the temporal distribution, geographical representation, topic evolution, and main trends within the data.

IV. Interactive Visualization Tools

In recent years, there has been a growing interest in the development of a suite of tools and features within interactive visual analysis systems across various fields such as visual analytics, information visualization, search behavior, and design management. These tools and features are specifically designed to enhance user interaction with data, support the analytical process through visual interaction systems, and facilitate deeper insights and understanding.

A. *Graph Search:*

Search functionality is a critical tool for navigating large volumes of data. The workings of graph search methods and auxiliary search features can be illustrated through diagrams, demonstrating how users can leverage these features during the search process to effectively locate specific information.

To assist users in the search process, it is necessary to integrate various search methods to meet different user preferences and needs. The initial search term is displayed at the center of the system as a node, with subsequent search terms presented as points of interest (POIs), each represented by nodes of different colors. The connections between nodes signify the relationships between search terms, and users can explore these relationships by clicking and dragging the nodes.

Users can quickly identify the relevance between pieces of information through graphical search. The system supports the expansion and refinement of user-defined search terms, allowing for an in-depth exploration of specific topics or concepts.

By adopting exploratory search methods, individuals can better cope with uncertainty and complexity, broaden their cognitive horizons, cultivate innovative capabilities, and discover new opportunities and solutions. Exploratory search methods hold significant importance in fields such as scientific research, business decision-making, technological innovation, and artistic creation, and can provide new inspiration and discovery for people. Overall, these methods and models aim to provide users with the tools and support needed to effectively explore and analyze complex datasets, enabling them to make informed decisions and gain insights from the data.

This visual design management technique effectively supervises and coordinates the goals, target audiences, brand guidelines, timelines, and budgets of visual design within a team or organization, guiding the direction of the project. Rapid ideation, prototyping, and testing of design solutions are facilitated. Regular design reviews and critiques ensure quality and efficiency, promoting collaboration and informed design decisions. The use of version control and collaboration tools can streamline workflows, allowing team members to work together, track changes, and maintain design consistency. By implementing these technologies, teams can enhance collaboration, simplify workflows, and deliver high-quality visual design solutions that effectively meet user needs and business objectives.

B. *Visualization of Points of Interest, POI:*

Points of Interest (POIs) refer to key concepts or data points defined by users during the search process that hold particular significance for their research or decision-making. In graphical search, POIs are indicated by highlighted circles, allowing users to obtain more relevant information by clicking on these circles or to use them as starting points for further searches. Users can add, remove, or modify Points of Interest, with the system updating the display results in real time to reflect changes within the dataset,just as show in figure 2.

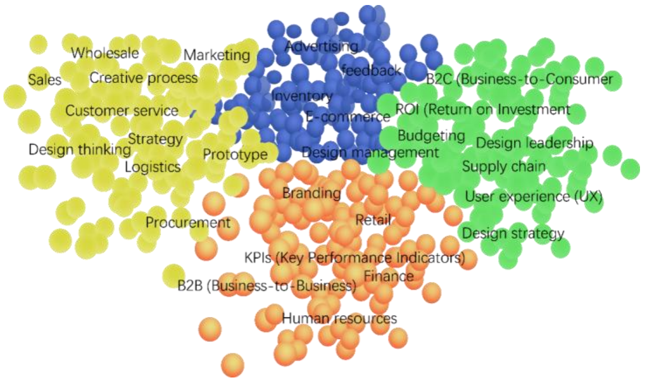

Fig. 2. Search point of interest word circles enhance search

C. Word Cloud:

Word clouds are a text data visualization tool used to display the frequency and significance of keywords within a large set of textual data. The size of each word in the word cloud represents its occurrence frequency within the dataset, and color can be used to differentiate between different topics or categories. Users can click on words within the word cloud to filter search results or to view relevant documents and contexts that include the word.

One innovative feature is the integrated "graphical search." By displaying the initial search term as a "circle in the center of the screen," this feature offers a novel way to visualize the search process. Users can then define further search terms as "Points of Interest" (POIs) and display them as small circles of specific colors [1]. This visualization allows users to easily see the relationships between different search terms and explore their connections. Figure 10 illustrates this concept.

The visual prominence of "keyword clouds" or keyword rendering highlights the "keywords" that frequently appear in web text. Word clouds filter through online text, enabling users to quickly grasp the main idea of an article(Figure 3).

Fig. 3. Personalized word cloud

This feature can assist users in narrowing down their search scope and more effectively locating specific information.

Overall, by integrating various search methods and functionalities such as Graph search, assisted search, and Advanced search, users can effectively navigate through vast amounts of data and efficiently find the information they require.

D. Temporal and Geographic Views:

The temporal view tool allows users to explore data based on the temporal dimension, such as observing the development and changes of a technological trend over time. The geographical view provides a means to display the distribution of data across different geographic locations, assisting users in identifying trends or patterns specific to certain areas.

Visualization methods enable users to gain insights, discover hidden relationships, and make informed decisions. Key components include leveraging various visualizations, providing interactive features for data manipulation, conducting trend analysis over time, facilitating data exploration, offering real-time updates, and supporting collaboration among users. This approach is valuable in industries such as business intelligence, market research, and healthcare, enabling organizations to gain meaningful insights, drive strategic decisions, and stay ahead of evolving trends.

At a macro level, a preliminary overview of emerging trends is conducted from the perspective of trend analysis. The emerging trends identified through topic modeling are visualized, presenting the most salient topics in the data in an engaging visual manner. This visualization assists users in quickly recognizing significant trends and patterns,as show in figure 4.

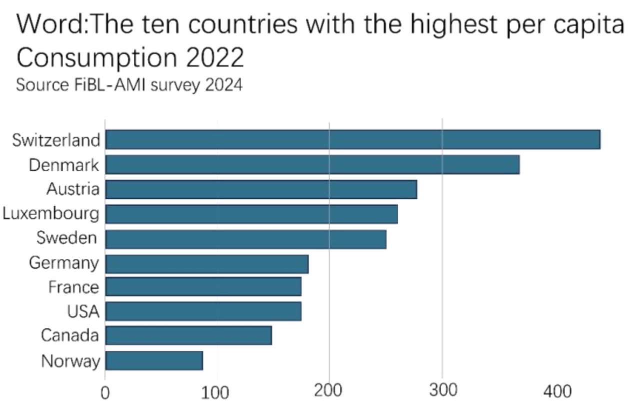

Fig. 4. Global market:The ten countries with the highest per capita consumption 2022

Source:FiBL-AMI survey 2024,based on data from government bodies,the private sector and market research companies for data sources,see annex,page 335.

E. Thematic Views:

The thematic view tool enables users to filter and view data based on specific topics or categories, which is highly useful for rapidly obtaining insights into particular domains.

Users can activate the thematic view by selecting or entering specific topic keywords, thereby obtaining relevant visual presentations and analyses as show in figure 5.

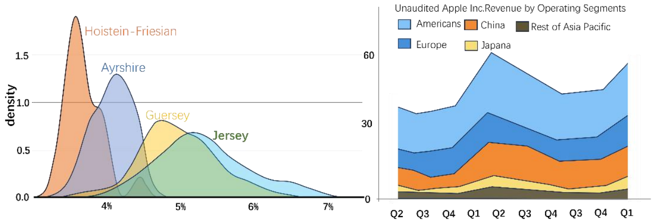

Fig. 5. Temporal visualization: left a river chart with a highlighted topic and right a stack river chart with the same highlighted topic. Both visual representations are using the same data

F. Integrated Visualization Dashboard:

The integrated dashboard provides a unified platform that combines all of the aforementioned interactive visualization tools, enabling users to employ multiple views and functionalities simultaneously. Users can tailor the dashboard to their individual needs and research objectives by selecting the most relevant tools and views. The dashboard supports collaborative work, allowing team members to share views, discuss findings, and make decisions collaboratively.

The integration of different visualization tools is a key aspect of data analysis because it allows users to answer specific questions based on different data models that serve as the underlying visualization structure. These visualization tools are designed to automatically detect the data models they support and require, and to visualize data in a user-friendly and informative manner [43, 44].

A key component of the visualization tools is the use of a semantic data model as the primary model, which serves as the foundation for other data models [45]. The semantic data model helps organize and construct data in a meaningful way, enabling users to effectively explore and analyze data.

Integrated visualizations encompass various visualization layouts, including temporal views, geographical views, semantic views, and thematic views, which are interactive and cater to different analytical tasks. These visualizations provide users with the ability to explore data from multiple perspectives and gain an in-depth understanding of patterns, trends, and relationships within the data. They can be based on visual similarity document layout analysis (DLA) schemes, utilizing clustering strategies that adaptively process documents of different languages, layout structures, and skew angles. By visually similar clustering, representative filters and statistics are found to characterize texture patterns in document images, thereby offering strong robustness and adaptability [46]. This feature enhances the user experience by providing a comprehensive overview of the data and allowing users to focus on specific data points of interest.

Integrated visualizations can be used both as a single interactive visualization interface and as components within an interactive dashboard to support a variety of analytical tasks[47]. This flexibility allows users to customize their data analysis process and tailor visualizations. The integration of different visualization tools with different data models provides users with a comprehensive interactive platform for effectively exploring and analyzing data.

Visualization and the overall user interface play a key role in enabling users to perform various tasks, with domain-specific tasks depending on the user and their particular needs and objectives. The interface is designed to facilitate analytical tasks aimed at strengthening corporate potential, identifying emerging trends, and predicting technological trajectories, as well as discovery tasks involving the detection of unexpected features, themes, technologies, or correlations in the data through aspect-oriented visualization.

One of the main tasks in the interface is to compare different databases to gain insights and make informed decisions. The user interface includes functionalities such as search, assisted search, faceted navigation, visual narrowing, and various visual selection areas to help users navigate and interact with data effectively, as show in figure 6.

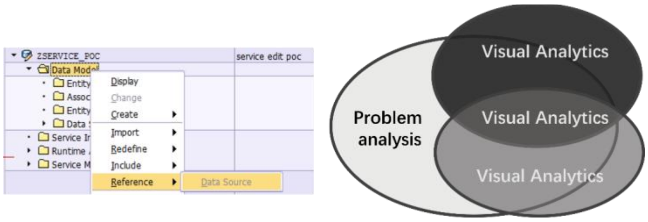

Fig. 6. Visual interactive application analysis

Users can narrow down search results to specific outcomes through search terms, graphical search, faceted navigation, and visual interaction. Additionally, they can compare result sets across different themes to understand variations and similarities within the data. The visualization tools within the interface allow for trend analysis of potential product innovations, enabling users to view emerging trends across different databases and make data-driven decisions.

Overall, the comprehensive user interface and visualization tools provide users with the means to effectively explore, analyze, and gain insights from data, enabling them to make informed decisions and drive innovation.

V. RESULTS AND DISCUSSION

The application of machine learning and data mining techniques in design management encompasses various aspects, including trend mining technologies, text mining and natural language processing, machine learning methods in interactive design, data visualization techniques, probabilistic topic models, data models and analytics, and interactive visualization tools. The utilization of these technologies' renders design management tools more intelligent and interactive, providing comprehensive data analysis and decision-making support.

Interdisciplinary integration will promote the convergence of technologies and methodologies from different disciplines in design management, enhancing the comprehensiveness and depth of decision-making. The development of real-time data and dynamic visualization enables users to acquire and analyze data more rapidly, accelerating the decision-making process. The application of augmented reality and virtual reality technologies offers a more immersive experience, assisting users in understanding data and information more intuitively. The evolution of collaboration and the sharing economy will foster teamwork and knowledge sharing, improving work efficiency and quality.

By integrating these technologies, a better understanding of user behavior, extraction of textual information, and analysis of trend changes can be achieved, providing effective support for enhancing the efficiency of the design process and the improvement of innovation capabilities.

In summary, the field of design management will continue to evolve and innovate driven by technology, offering users better data analysis and decision support.

VI. CONCLUSIONS

With the rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) technologies, design tools are not only capable of intelligently meeting user needs but also provide in-depth data analysis and predictive capabilities, thereby assisting enterprises and users in making more precise strategic decisions. In this process, interdisciplinary integration plays a crucial role by integrating technologies and methods from different disciplines, significantly enhancing the comprehensiveness and depth of decision-making.

The development of real-time data streams and dynamic visualization tools has greatly accelerated the speed of data acquisition and analysis, thereby hastening the entire decision-making process. Moreover, the application of Augmented Reality (AR) and Virtual Reality (VR) technologies has brought an immersive experience to design management, allowing users to understand complex data and information more intuitively. The rise of collaboration and the sharing economy has promoted teamwork and knowledge sharing, further improving work efficiency and quality.

In the field of technology and innovation management, literature reviews, trend visualization, interactive visualization, and interactive design methods are essential for constructing technology management and visualization analysis systems. These methods not only help identify gaps and challenges in the research field but also enable users to quickly identify patterns and trends by transforming complex data into intuitive graphical representations. Interactive design methods particularly emphasize the central role of users in the design process, ensuring that the system can meet user needs and support the effective identification and utilization of emerging technological trends.

The interactive design-based approach proposed in this paper, which combines information visualization, trend mining, and interactive design, not only enhances and expands previous methods of technology and design management trend analysis but also introduces novel interactive designs, providing more suitable interactive methods for technology foresight and innovation detection. These methods and tools enable enterprises to respond more effectively to market changes, grasp technological trends, and make wise strategic decisions.

In summary, the field of design management continues to evolve and innovate driven by technology. From trend mining technologies to machine learning methods in interactive design, to data visualization techniques, and the application of probabilistic topic models, the integrated use of these technologies provides users with better data analysis and decision support. As personalized and adaptive systems further develop, and as AI and ML technologies continue to advance, design management tools will become more intelligent, better able to meet user needs, and offer more in-depth data analysis and predictive capabilities. The future of design management will be a highly integrated, intelligent, and user-centered field, constantly pushing the boundaries of innovation and bringing unprecedented value to users and enterprises.

References

[1] Nazemi, K., D. Burkhardt, and A. Kock, Visual analytics for technology and innovation management. Multimedia Tools and Applications, 2022. 81(11): p. 14803-14830.

[2] Hosseini Dolatabad, A., et al., Supplier selection in the industry 4.0 era by using a fuzzy cognitive map and hesitant fuzzy linguistic VIKOR methodology. Environmental Science and Pollution Research, 2023. 30(18): p. 52923-52942.

[3] Euchner, J., Advancing the State of Practice. Research-Technology Management, 2017. 60(1): p. 9-10.

[4] Qi, W., et al., An adaptive reinforcement learning-based multimodal data fusion framework for human–robot confrontation gaming. Neural Networks, 2023. 164: p. 489-496.

[5] Ying, W., et al., Research on emotional interaction and user cognition. International Conference on Computer Science and Communication Technology (ICCSCT 2023). Vol. 12918. 2023: SPIE.

[6] Zhang, J., Y. Sun, and C. Yao, Semantically linking events for massive scientific literature research. The Electronic Library, 2017. 35(4): p. 724-744.

[7] Grewal, D., et al., The Future of Digital Communication Research: Considering Dynamics and Multimodality. Journal of Retailing, 2022. 98(2): p. 224-240.

[8] Ogiela, M.R., W. Rahayu, and F. Palmieri, Human oriented solutions for intelligent analysis, multimedia and communication systems. Concurrency and Computation: Practice and Experience, 2021. 33(19): p. e6532.

[9] Vohra, A. and R. Garg, Deep learning based sentiment analysis of public perception of working from home through tweets. Journal of Intelligent Information Systems, 2023. 60(1): p. 255-274.

[10] Saad, E., et al., Determining the Efficiency of Drugs Under Special Conditions From Users' Reviews on Healthcare Web Forums. IEEE Access, 2021. 9: p. 85721-85737.

[11] Taherdoost, H., Deep Learning and Neural Networks: Decision-Making Implications. Symmetry, 2023. 15(9): p. 1723.

[12] Chin, G., et al., Visual Analysis of Dynamic Data Streams. Information Visualization, 2009. 8(3): p. 212-229.

[13] Pour Rahimian, F., et al., OpenBIM-Tango integrated virtual showroom for offsite manufactured production of self-build housing. Automation in Construction, 2019. 102: p. 1-16.

[14] Frank, L., et al., Design heuristics for customer-centric business processes. Business Process Management Journal, 2020. 26(6): p. 1283-1305.

[15] Grenha Teixeira, J., et al., The MINDS Method:Integrating Management and Interaction Design Perspectives for Service Design. Journal of Service Research, 2017. 20(3): p. 240-258.

[16] Qiu, Q., et al., Automatic spatiotemporal and semantic information extraction from unstructured geoscience reports using text mining techniques. Earth Science Informatics, 2020. 13(4): p. 1393-1410.

[17] Pecman, M., Variation as a cognitive device: How scientists construct knowledge through term formation. Terminology. International Journal of Theoretical and Applied Issues in Specialized Communication, 2014. 20(1): p. 1-24.

[18] Khan, O.A., et al., Keyword Extraction for Medium-Sized Documents Using Corpus-Based Contextual Semantic Smoothing. Complexity, 2022. 2022: p. 7015764.

[19] Sciascio, C.D., et al., Interactive Quality Analytics of User-generated Content: An Integrated Toolkit for the Case of Wikipedia. ACM Trans. Interact. Intell. Syst., 2019. 9(2–3): p. Article 13.

[20] Bharath Bhushan, S.N. and A. Danti, Classification of text documents based on score level fusion approach. Pattern Recognition Letters, 2017. 94: p. 118-126.

[21] Nicolas, G., X. Bai, and S.T. Fiske, Comprehensive stereotype content dictionaries using a semi-automated method. European Journal of Social Psychology, 2021. 51(1): p. 178-196.

[22] Cao, H., et al., A Hotspot Information Extraction Hybrid Solution of Online Posts' Textual Data. Scientific Programming, 2021. 2021: p. 6619712.

[23] Wang, H.C., Y.C. Chi, and P.L. Hsin, Constructing Patent Maps Using Text Mining to Sustainably Detect Potential Technological Opportunities. Sustainability, 2018. 10(10): p. 3729.

[24] Cammarano, A., F. Michelino, and M. Caputo, Extracting firms' R&D processes from patent data to study inbound and coupled open innovation. Creativity and Innovation Management, 2022. 31(2): p. 322-339.

[25] Azmi, A.M., A.O. Al-Qabbany, and A. Hussain, Computational and natural language processing based studies of hadith literature: a survey. Artificial Intelligence Review, 2019. 52(2): p. 1369-1414.

[26] Oralbekova, D., et al., Contemporary Approaches in Evolving Language Models. Applied Sciences, 2023. 13(23): p. 12901.

[27] Schmidt, J., et al., Popup-Plots: Warping Temporal Data Visualization. IEEE Transactions on Visualization and Computer Graphics, 2019. 25(7): p. 2443-2457.

[28] Scaccia, J.P. and V.C. Scott, 5335 days of Implementation Science: using natural language processing to examine publication trends and topics. Implementation Science, 2021. 16(1): p. 47.

[29] Dowling, M., et al., Interactive Visual Analytics for Sensemaking with Big Text. Big Data Research, 2019. 16: p. 49-58.

[30] Wójcik, M., Areas and contexts of the use of robotics in libraries: an overview of the applied solutions and a discussion of prospects. Library Hi Tech, 2023. ahead-of-print(ahead-of-print).

[31] Huang, Y., et al., Early insights on the Emerging Sources Citation Index (ESCI): an overlay map-based bibliometric study. Scientometrics, 2017. 111(3): p. 2041-2057.

[32] Punetha, N. and G. Jain, Optimizing Sentiment Analysis: A Cognitive Approach with Negation Handling via Mathematical Modelling. Cognitive Computation, 2024. 16(2): p. 624-640.

[33] Tseng, H.-W., et al., An efficient error prevention and recovery scheme for multicast traffic in data center networks. Journal of Network and Computer Applications, 2018. 114: p. 38-47.

[34] Alexakis, C., et al., Textual Machine Learning: An Application to Computational Economics Research. Computational Economics, 2021. 57(1): p. 369-385.

[35] 35. Ihou, K.E., M. Amayri, and N. Bouguila, Stochastic Variational Optimization of a Hierarchical Dirichlet Process Latent Beta-Liouville Topic Model. ACM Trans. Knowl. Discov. Data, 2022. 16(5): p. Article 84.

[36] Altarturi, H.H.M., M. Saadoon, and N.B. Anuar, Web content topic modeling using LDA and HTML tags. PeerJ Computer Science, 2023. 9: p. e1459.

[37] Qian, Y., Mining culture from professional discourse: a lexicon-based hybrid method. Language Resources and Evaluation, 2023. 57(3): p. 945-961.

[38] Wang, X., et al., A general framework for big data knowledge discovery and integration. Concurrency and Computation: Practice and Experience, 2018. 30(13): p. e4422.

[39] Ramay, W.Y., et al., Hybrid approach for big data localization and semantic annotation. Concurrency and Computation: Practice and Experience, 2021. 33(4): p. e4955.

[40] Di Lorenzo, D., et al., Data Completion, Model Correction and Enrichment Based on Sparse Identification and Data Assimilation. Applied Sciences, 2022. 12(15): p. 7458.

[41] Zhang, J.D. and C.Y. Chow, TICRec: A Probabilistic Framework to Utilize Temporal Influence Correlations for Time-Aware Location Recommendations. IEEE Transactions on Services Computing, 2016. 9(4): p. 633-646.

[42] Aoidh, E.M., M. Bertolotto, and D.C. Wilson, Understanding geospatial interests by visualizing map interaction behavior. Information Visualization, 2008. 7(3-4): p. 275-286.

[43] Fadloun, S., et al., Visual Analytics Using Machine Learning for Transparency Requirements. Mathematics, 2023. 11(14): p. 3091.

[44] Orlando, D., et al., TGV: A Visualization Tool for Temporal Property Graph Databases. Information Systems Frontiers, 2023.

[45] Chen, L., Z. Liu, and M. Ma, Interactive Visualization of Geographic Vector Big Data Based on Viewport Generalization Model. Applied Sciences, 2022. 12(15): p. 7710.

[46] Wen, D. and X.-Q. Ding, Visual Similarity Based Document Layout Analysis. Journal of Computer Science and Technology, 2006. 21(3): p. 459-465.

[47] Shakeel, H.M., et al., A Comprehensive State-of-the-Art Survey on Data Visualization Tools: Research Developments, Challenges and Future Domain Specific Visualization Framework. IEEE Access, 2022. 10: p. 96581-96601.